Students' Motivational Trajectories and Academic Success in Math-Intensive Study Programs: Why Short-Term Motivational Assessments Matter

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Abstract

Students' expectancy-value beliefs play an important role in shaping their educational choices and behaviors. Drawing on Eccles et al.'s situated expectancy-value theory, we investigated short-term changes in students' expectancy-value beliefs in gateway math courses for beginning university students. In Study 1a, we collected data from first-semester students in three math-intensive study programs at the beginning, midpoint, and end of the semester (*N* = 1,004). Latent change score analyses revealed a significant decline in students' expectancy, intrinsic value, and utility value, and an increase in perceived psychological and effort costs over the first half of the semester. These maladaptive motivational changes predicted students' end-of-term study program satisfaction, exam performance, and course dropout. Study 1b then explored weekly motivational changes in the very first weeks of the semester using a subsample from Study 1a (*N* = 773). We found that students experienced a "motivational shock" between Weeks 2 and 3 of the semester that coincided with their first performance feedback on mandatory math worksheets. The motivational shock was characterized by a rapid decline in students' intrinsic and utility values, and a significant increase in their perceived cost. Similar to Study 1a, the motivational shock in Study 1b predicted students' end-of-term study program satisfaction, exam performance, and course dropout. Across both studies, female students and students with comparatively lower prior achievement experienced more negative motivational changes. Our studies underscore the importance of considering short-term motivational changes as early warning signs of academic struggles and course dropout in math-intensive fields.

Keywords: motivational changes, situated expectancy-value theory, STEM, academic achievement, dropout tendencies

Educational Impact and Implications Statement

The present study focused on short-term changes in students' academic motivations during their first semester in math-intensive study programs, which are often plagued by particularly high dropout rates. Our analyses revealed significant declines in students' academic motivations in the first weeks of the semester. These motivational declines were a precursor to academic struggles at the end of the first semester at the university (lower study program satisfaction and achievement, higher likelihood of course dropout). Our results suggest that educational interventions that support students' success in math-intensive study domains are needed in the very early stages of their college careers.

Students' Motivational Trajectories and Academic Success in Math-Intensive Study Programs: Why Short-Term Motivational Assessments Matter

Nationally and internationally, there are concerns about the insufficient involvement of talented youth in math-intensive fields such as science, technology, engineering, and mathematics (STEM; Organisation for Economic Co-operation and Development [OECD], 2019; President's Council of Advisors on Science and Technology, 2012). On average, only approximately 27% of bachelor's degree students in OECD member countries choose to pursue a degree in a STEM field (Chen, 2013; OECD, 2019). Furthermore, a relatively high percentage of students who enroll in math-intensive programs drop out, i.e., they leave without completing a degree (Chen, 2013; Heublein & Schmelzer, 2018). In Germany, where our research was conducted, dropout rates in math-intensive programs such as physics, engineering, and mathematics range between 35% and 54% (Heublein & Schmelzer, 2018). Student dropout can incur significant personal and societal costs, including interrupted educational trajectories, lost career opportunities, and psychological strain (Faas et al., 2018; OECD, 2019; Schneider & Yin, 2011). It is therefore important to understand what factors contribute to students' academic struggles and dropout tendencies, especially in math-intensive fields.

Expectancy-value theory provides a powerful framework that describes the motivational underpinnings of achievement-related choices such as the decision to pursue a degree in, persist, or drop out of a STEM program (Eccles et al., 1983; Guo et al., 2015; Lauermann et al., 2017; Perez et al., 2014). Evidence suggests that students' expectancy beliefs ("Can I do this task?") and subjective task values ("Do I want to do this task?") are predictive of their achievement-related choices and behaviors, even when differences in cognitive abilities are accounted for (e.g., Perez et al., 2014; for a review, see Wigfield & Cambria, 2010). Longitudinal research further indicates that students' expectancy beliefs and task values decline—on average—across their educational careers (e.g., Jacobs et al., 2002; Robinson et al., 2019). These motivational declines can be a precursor to later academic struggles and dropout from math-intensive educational and occupational fields (e.g., Gaspard et al., 2020; Robinson et al., 2019). Importantly, recent research indicates that these motivational beliefs are malleable and can thus be targeted in interventions that improve students' participation and persistence in STEM (e.g., Gaspard, Dicke, Flunger, Brisson, et al., 2015; for a review, see Rosenzweig & Wigfield, 2016).

However, our understanding of students' motivational trajectories in math-intensive fields is still limited, especially in the context of higher education. First, most of the available research has examined changes in students' motivations using annual assessments of expectancies and subjective task values (e.g., Jacobs et al., 2002; Watt, 2004), and only a few studies have explored short-term changes in these beliefs (e.g., over the course of a semester or at critical time points such as the transition to higher education; Dresel & Grassinger, 2013; Kosovich et al., 2017). Yet, short-term declines in students' expectancy and value beliefs—especially at the beginning of college—are a precursor to later declines in academic performance, and can thus function as early warning signs of academic struggles and intentions to leave college (Kosovich et al., 2017; Perez et al., 2014). Second, even fewer studies have examined these short-term motivational changes in math-intensive fields where dropout tendencies are particularly severe (Heublein & Schmelzer, 2018). Third, the available evidence is often limited to two or three measurement points during the semester (for an exception, see Johnson et al., 2014); however, more intensive short-term assessments are necessary to better understand the development of students' motivations at critical time points such as the transition to higher education when motivational changes are particularly likely (Eccles & Midgley, 1989). Finally, existing research has focused almost exclusively on a single course or study program (Kosovich et al., 2017; Zusho et al., 2003), which might limit the generalizability of the reported findings.

To address these gaps in the literature, the present study examined short-term changes in students' expected academic success and subjective task values in three math-intensive study programs shortly after the transition to higher education. We focused not only on semester-long motivational changes but also on weekly fluctuations in students' motivations at the beginning of the semester and were thus able to conduct fine-grained analyses of students' experiences at a critical stage in their educational careers. Prior evidence suggests that the majority of students who drop out of higher education do so within the first year of their study program (Heublein & Schmelzer, 2018; OECD, 2019). Furthermore, we focused on required math courses that typically function as a gatekeeper to further engagement and success in math-intensive study programs. Academic struggles and low levels of motivation in such courses have been identified as one of the most critical factors influencing students' decision to drop out of STEM (Heublein et al., 2017; Seymour & Hewitt, 1997).

In the following sections, we discuss new developments in Eccles' expectancy-value theory that specifically focus on students' situational motivations, and we describe potential predictors and consequences of short-term fluctuations in students' academic motivations for their subsequent academic success and well-being.

Expectancy-Value Theory and Developmental Trajectories of Student Motivation: A Situational Perspective

Expectancy-value theory (Eccles et al., 1983) posits that students' expected success in academic domains such as math and science and their subjective valuing of these domains are proximal predictors of important achievement-related choices and behaviors such as students' educational and career decisions, persistence in the face of difficulty, and academic performance (for a review, see Wigfield et al., 2016). A key contribution of this theoretical framework is the differentiation of expectancy and task value components that shape students' domain- and task-specific choices and behaviors such as the decision to persist in or drop out of the STEM domain. The theory distinguishes between students' self-concepts of ability in different academic domains and their task- and time-specific expected success (Eccles & Wigfield, 1995, 2020; Wigfield & Eccles, 2000). Students' self-concepts reflect relatively stable beliefs about their ability in particular domains such as math or science, whereas expectancy refers to students' subjective probability of success on a given task or domain (e.g., an exam or a course assignment). Although these two constructs have often been combined into one composite score, Eccles and Wigfield (2020) point out that they are conceptually distinct and may follow different developmental trajectories. Much of the expectancy-value literature has focused on students' self-concepts of ability (e.g., Jacobs et al., 2002; see also Wigfield & Cambria, 2010), and less is known about the relevance of their task- and time-specific expectancy beliefs for their academic success and well-being (Dietrich et al., 2019; Tanaka & Murayama, 2014).

Additionally, Eccles and colleagues differentiated several components of students' subjective task values (Eccles et al., 1983; Wigfield & Eccles, 2000; Wigfield & Eccles, 2020): Individuals may value a given task or activity because of its importance for one's identity (attainment value), because of the interest in or enjoyment of engaging in the task (intrinsic value), or because of its usefulness for current or future goals (utility value). These three value components address potential reasons for engaging in a given task, whereas the cost component refers to perceived drawbacks (Eccles et al., 1983; Wigfield & Eccles, 2020). Engagement in a given task or activity may be perceived as subjectively costly due to the perceived amount of effort required to be successful (effort cost), concerns about missed opportunities to engage in alternative valued activities or tasks (opportunity cost), and negative emotions that stem from anticipated or experienced failure (psychological cost;

Eccles et al., 1983; Perez et al., 2014; Wigfield & Eccles, 2020, see also Flake et al., 2015). As noted previously, these motivational constructs have emerged as powerful predictors of students' educational and occupational choices and behaviors, including students' enrollment in high school courses (Wang, 2012), career aspirations in math- or science-related fields (Nagengast et al., 2011), enrollment in particular college majors (Gaspard et al., 2019), college retention (Robinson et al., 2019) and career attainment in STEM (Lauermann et al., 2017).

Recently, Eccles and Wigfield (2020) pointed out that students' expectancy and subjective task values are not only developmental (i.e., change over time) but also situationally sensitive (i.e., influenced by situational characteristics). Differences in the salience of situational characteristics such as task difficulty or the number of options for action of which a given individual is aware can change the perceived relevance of different value facets, and thus, these facets can carry different weights in influencing students' decision-making at a given point in time. A student's interest in math, for example, might be a key driving force behind choosing to pursue a degree in a STEM field, whereas the cost component might become an increasingly influential determinant of the student's subjective valuing of this domain when he or she faces typical challenges such as demanding coursework or a difficult exam. Accordingly, expectancy-value research should focus not only on the developmental course and long-term implications of these motivational constructs for students' academic choices and behaviors but also on situation-specific influences that shape students' time- and task-specific decision-making (Eccles & Wigfield, 2020; Wigfield & Eccles, 2020). Eccles and Wigfield emphasized the situational nature of the expectancy-value constructs in their theoretical framework by renaming their theory *situated expectancy-value theory* (SEVT; Eccles & Wigfield, 2020).

Educational research on situation-specific motivational fluctuations is still relatively scarce; therefore, it is not yet clear whether, when, and for whom these fluctuations can serve as an early warning sign of academic struggles. Research focusing on long-term developmental processes has typically documented an average decline in students' academic motivations over time (Chouinard & Roy, 2008; Jacobs et al., 2002; Robinson et al., 2019; Watt, 2004), but evidence focusing on short-term motivational changes is less consistent. Several studies have observed short-term declines in students' motivational beliefs that parallel previously documented long-term declines (Dresel & Grassinger, 2013; Kosovich et al., 2017; Perez et al., 2014; Sonnert et al., 2015; Zusho et al., 2003), but other studies have found no change (Hardin & Longhurst, 2016) or an increase in students' motivations (Bong, 2005; Finney & Schraw, 2003). A number of factors might contribute to these mixed results. First, both ability-related and task value-related motivations are more likely to fluctuate over time when they are measured with situation-specific assessments that reference students' lesson-, class- or content-specific expectancies and values (Dietrich et al., 2017; Tanaka & Murayama, 2014; Tsai et al., 2008), as opposed to more global motivations such as students' domain-specific self-concepts of ability and interests (Hardin & Longhurst, 2016; Jansen et al., 2020; Rieger et al., 2017).

Second, some motivational constructs might be more sensitive to situational influences than others, and different constructs can follow different developmental trajectories. For instance, over the course of a semester in an introductory psychology course, Kosovich et al. (2017) found a greater decline in students' expectancy beliefs than in their utility value, and this decline was predicted by students' performance over the course of the semester. Similarly, in a chemistry course for beginning students, Perez et al. (2014) found a greater decline in students' competence beliefs than in their task values (a composite of intrinsic, utility, and attainment value). Perez et al. (2014) also observed a greater increase in students' perceived effort and opportunity cost than in their perceived psychological cost (effort cost emerged as one of the strongest predictors of dropout intentions in this study). Unfortunately, very few studies to date have examined multiple facets of the expectancy-value framework with situation-specific assessments in the same sample, which limits our ability to examine differential developmental trajectories within the same sample and across different situations. Furthermore, with very few exceptions (Perez et al., 2014; Perez et al., 2019), the cost component has been largely neglected in this literature, despite its potential to explain interindividual differences in students' academic achievement and dropout intentions. In the present study, we examine the short-term trajectories of students' expectancy, intrinsic and utility values as well as perceived psychological and effort costs.

Finally, motivational changes can be time specific. For instance, Zusho et al. (2003) reported a decline in students' confidence in their ability to master achievement tasks in introductory chemistry courses from the beginning to the midpoint of the semester but found no further changes in these beliefs towards the end of the semester (see also Hardin & Longhurst, 2016). A period of adaptation may have contributed to this developmental pattern. In addition, motivational changes may be particularly likely at educational transitions because students face new academic demands and have to adjust to a new and unfamiliar educational context (Eccles & Midgley, 1989). To date, most studies of students' short-term motivational changes in higher education have assessed students' motivations only at the beginning and at the end of a given course or semester, and thus, these studies do not sufficiently account for a period of adaptation between these time points. Further research that examines construct- and time-specific differences in students' educational experiences is warranted.

Predictors of Motivational Changes: The Role of Prior Achievement, Gender, Family Background, and Course-Specific Differences

One of the strongest predictors of students' expectancy beliefs and subjective task values is their prior academic performance, which is often operationalized via standardized test scores or grades (e.g., Perez et al., 2014; Robinson et al., 2019). Evidence suggests that students' prior academic achievement in school typically serves as a buffer against motivational declines in college (Robinson et al., 2019; Sonnert et al., 2015). In our study, we focus on students' high school grade point average (GPA) as an indicator of prior performance for several reasons. Students' GPA predicts important life outcomes such as academic success (e.g., degree completion), career success (e.g., wages), and general life satisfaction, even when differences in intelligence and standardized performance are controlled for (Borghans et al., 2016; see also Allensworth & Clark, 2020; Schneider & Preckel, 2017). Furthermore, students' grades are more strongly correlated with their academic motivations than are students' standardized performance or intelligence (Borghans et al., 2016; Lauermann et al., 2020). Finally, German institutions of higher education use students' high school GPA as a selection criterion for college admission (Heublein et al., 2017), and no standardized admission tests (analogous to the SAT or ACT in the US) are available in this educational context.

Even when there are no or only small differences in achievement, prior research has revealed persistent gender differences in STEM-related motivations and educational attainment (OECD, 2019; Wang & Degol, 2017). Gender differences are particularly pronounced in the most math-intensive STEM fields such as physics and math (OECD, 2019), and some studies report higher dropout rates from math-intensive study programs for female students than for male students (Griffith, 2010; Isphording & Qendrai, 2019). With some exceptions (e.g., Lauermann et al., 2017), evidence suggests that compared to male students, female students report lower levels of competence beliefs, intrinsic value, and utility value in the math domain, as well as higher levels of subjective cost (Gaspard, Dicke, Flunger, Schreier, et al., 2015; Nagy et al., 2010; Watt, 2004). However, analyses of situation-specific rather than general math-related motivations and affect (e.g., interest and anxiety) tend to reveal smaller or no gender differences (Goetz et al., 2013; Tsai et al., 2008). Accordingly, male and female students' everyday experiences in the math domain might be more similar than is typically assumed in research that relies on relatively global self-assessments of academic motivation and affect.

Students' family background (i.e., socioeconomic status, SES) is yet another important factor that can influence their decision to pursue higher education, their subsequent academic success, and the likelihood of dropping out of college (Isleib, 2019; Parker et al., 2012; Sackett et al., 2009). Notably, students from different family backgrounds often report similar expectancy beliefs and subjective task values at the beginning of college (Robinson et al., 2019) but achieve different educational and occupational attainments (e.g., achievement, level of job prestige; OECD, 2019; Schoon & Polek, 2011). A number of factors contribute to these social disparities, including differences in the quality of educational opportunities in K-12 schooling, insufficient access to information about performance requirements, financial struggles, and competing time commitments such as employment, which can increase the risk of college dropout (Isleib, 2019; Walpole, 2003).

Finally, students' academic motivations are likely to vary as a function of course- and context-specific influences (e.g., Mac Iver et al., 1991). Some motivational changes may be universal (e.g., motivational declines at educational transitions), whereas others might be course- and context-specific, for instance, due to different instructional and assessment practices (Linnenbrink-Garcia et al., 2016). However, most studies to date have focused on a single course or study program so that the generalizability of identified motivational declines across different courses and study programs remains unclear. Examining students' math-related motivational trajectories across different courses and study programs in the present study allows us to address this gap and identify patterns of motivational change that are relatively generalizable across different math-intensive courses and study programs.

Relatedly, assessment practices such as receiving performance feedback may affect students' motivational trajectories. Prior research has shown that people are often overconfident with respect to their expected performance across a variety of cognitive tasks (Metcalfe, 1998), for instance, their expected grade in introductory economics and quantitative courses in college (Nowell & Alston, 2007). This overconfidence bias may be particularly relevant after the transition to a new educational context such as math-intensive study programs in college: Students' expectations of their performance may not yet be calibrated to the high demands and performance requirements of such programs. Accordingly, receiving performance feedback for the first time may be a precursor to motivational declines.

Motivational Changes as a Predictor of Students' Academic Success

As noted previously, extensive research in the expectancy-value literature corroborates the importance of students' expectancy and subjective task values as proximal psychological predictors of their achievement, effort investment, and persistence in the pursuit of challenging academic goals, even when the effects of background characteristics such as gender or prior achievement are controlled for (for a review, see Wigfield & Cambria, 2010). Substantial evidence indicates that students' motivations and their academic achievement influence each other over time (e.g., Marsh & Martin, 2011; Weidinger et al., 2020). Students' domain-specific self-concepts of ability and their subjective task values predict later academic achievement even after controlling for differences in prior achievement (e.g., Robinson et al., 2019; Steinmayr & Spinath, 2009). Students' motivations are thus key predictors of their academic success in math-intensive fields and play a particularly important role in students' academic success in required gateway courses (Perez et al., 2014). Such courses are critical for students' long-term academic success because they are a prerequisite for enrollment in subsequent courses, students' degree completion, and further engagement in STEM fields (Seymour & Hewitt, 1997).

Importantly, students' academic success is not limited to their academic performance. Affective-motivational aspects such as students' study program satisfaction are also important because they reflect students' well-being in a given academic environment and can be a precursor to later job satisfaction (Nauta, 2007). Students' overall study program satisfaction—i.e., their satisfaction with various aspects of their academic life in a particular field of study—has been linked to their academic achievement (Nauta, 2007), long-term persistence (Lent et al., 2016), and retention in college (Starr et al., 1972). Assessments of students' study program satisfaction typically include components similar to those used to assess job satisfaction (Westermann et al., 1996). These assessments capture students' overall satisfaction with or enjoyment of their studies, satisfaction with the choice of their study program or university, and satisfaction with the content taught in their study program (Nauta, 2007; Westermann et al., 1996). Numerous studies suggest that students' domain- and context-specific academic motivations are key predictors of their overall study program satisfaction and dropout intentions (e.g., Bergey et al., 2018; Perez et al., 2014; Wach et al., 2016). Comparatively few studies have examined students' expectancy-value beliefs as predictors of dropout or retention in college (e.g., Robinson et al., 2019). For instance, Robinson et al. (2019) found that changes in students' expectancy-value beliefs across the first two years in college predicted students' retention in an engineering major at the end of the second year in college. However, we are not aware of any studies that have examined students' expectancy-value beliefs as predictors of course dropout in gateway math courses.

In the present study, we examined potential associations between short-term motivational changes at the beginning of the semester and end-of-term exam performance, study program satisfaction, and course dropout.

Indeed, several studies indicate that short-term motivational changes might serve as early warning signs of later academic struggles and dropout intentions in college (Dresel & Grassinger, 2013; Kosovich et al., 2017; Zusho et al., 2003). For instance, in two introductory chemistry courses, Zusho et al. (2003) found that declines in students' self-efficacy and overall task value across three time points during the semester were related to lower levels of end-of-term exam performance. Similarly, significant declines in students' general academic self-concept and task value from the beginning to the end of the semester predicted their dropout intentions at the end of the semester across different study programs at a German university, even when differences in prior achievement (i.e., high school GPA) were statistically controlled for (Dresel & Grassinger, 2013). However, no study to date has examined potential differences in students' short-term motivational trajectories between different task value facets; thus, little is known about whether some facets might be more likely to change than others, and whether such changes might thus serve as warning signs of later academic struggles. Furthermore, with only one exception (Johnson et al., 2014), the available research in higher education has typically focused on two or three time points during the semester, thus providing limited information about the shape of students' motivational trajectories or potentially sensitive time points at which motivational declines are most likely to occur. More intensive, short-term analyses can help us to identify the time points at which motivational interventions might be most fruitful and needed (Rosenzweig & Wigfield, 2016).

The Present Research

The present research (Study 1a and Study 1b) expands upon prior evidence by examining short-term changes in students' expectancy and subjective task values over the course of a semester in gateway math courses in math, physics, and math teacher education programs at a German university. In Study 1a, we examine changes in students' motivations across three time points during the semester (beginning [T1], midpoint [T5], and end of term [T6]) and their links to indicators of students' academic success (end-of-term study program satisfaction, final exam performance, and course dropout). In Study 1b, we focus on a subsample of students from Study 1a and examine weekly and situation-specific changes in students' motivations in four consecutive weeks at the beginning of the semester (T1–T4). Analyses in Study 1b thus focus on the developmental trajectories of students' motivations shortly after the transition to higher education and examine their predictive effects on students' end-of-term performance, study program satisfaction, and course dropout.

Three research questions (RQs) guide our analyses. First (RQ#1), how do students' expectancy, intrinsic and utility values, and psychological and effort costs change throughout the semester (Study 1a) as well as during the very first weeks of the semester (Study 1b)? These analyses allow us to identify particularly sensitive time points at which motivational changes are most likely to occur, whether these changes are temporary and reversible or might serve as warning signs of later academic struggles, and whether different expectancy-value constructs change at the same rate. Due to survey length constraints, we were not able to include all possible task values. We focused on intrinsic and utility values because they have been shown to change more than other values (e.g., attainment value) over short periods of time in college samples (e.g., two years; Robinson et al., 2019). Furthermore, we examined changes in psychological and effort cost: The perceived psychological cost may be particularly likely to change shortly after the transition to higher education in math-intensive study programs because students need to adapt to the high workload and new demands (Seymour & Hewitt, 1997). In addition, effort cost has emerged as a key predictor of students' dropout intentions and retention in STEM majors (Perez et al., 2014; Robinson et al., 2019).

Based on prior research (e.g., Kosovich et al., 2017; Perez et al., 2014), in Study 1a, we expect students' expectancy and task values to decrease and their perceived cost to increase over the semester. We make no specific predictions about the shape of students' motivational trajectories within the four-week period in Study 1b. Potential changes in students' motivations from week to week might represent content-specific, momentary shifts in motivation as students are adjusting to an unfamiliar academic environment, or these changes might be an early sign of academic difficulties. Due to the scarcity of prior research on short-term motivational changes, we refrain from formulating specific predictions regarding differences in the trajectories between the five expectancy-value facets assessed in our study. The few prior studies that are available to date have either found greater changes in students' expectancy or competence-related beliefs than in their task values (Kosovich et al., 2017; Perez et al., 2014; Perez et al., 2019) or similar rates of change (Dresel & Grassinger, 2013). However, these prior findings may not apply to the context of our study, which was conducted in gateway math courses in math-intensive study programs. Students in such programs need to adapt to a high workload and to new math content that is often vastly different from the type of math that is being taught in high school (i.e., learning math as a scientific discipline vs. applied math taught in high school; Gueudet, 2008).

Second (RQ#2), to what extent are students' motivational trajectories related to their individual and family background characteristics (gender, high school GPA, SES), and their specific math course and study program? These analyses allow us to investigate whether and to what extent preexisting differences in students' characteristics, as well as their course-specific experiences, affect students' motivations and subsequent academic outcomes. Some motivational shifts may be universal (e.g., resulting from students' need to adapt to a new context), but others might be context specific or specific to particular groups of students (e.g., as a function of gender, prior achievement, or SES). If there are gender differences in students' motivational trajectories, we expect these differences to favor male over female students (e.g., Sonnert et al., 2015). In line with prior research (Robinson et al., 2019; Sonnert et al., 2015), we also expect that students' high school GPA and SES will function as protective factors against potential motivational declines. Because the math courses were taught by different instructors and across different study programs, we included dummy variables to capture course-specific differences in students' motivations and academic outcomes. In addition, some students in our study had participated in preparatory math courses prior to course enrollment; participation in such preparatory courses was included as a control variable in all analyses.[1]

Third (RQ#3), can short-term changes in students' expectancy-value beliefs serve as warning signs of later academic struggles, i.e., do motivational changes predict students' achievement on their final exam, self-reported study program satisfaction at the end of the semester, and course dropout? We expect that students with comparatively more positive motivational trajectories will perform better on the final exam, will be more satisfied with their study program, and will be less likely to drop out of their math course towards the end of the semester (cf. Dresel & Grassinger, 2013; Kosovich et al., 2017; Robinson et al., 2019). The same research questions were examined in both studies, focusing either on motivational changes across the entire semester (Study 1a) or the first weeks of the semester (Study 1b).

[1] Such preparatory courses are typical for math-intensive programs at German universities, are free of charge for all admitted students, and may be a buffer against a potential motivational decline.

Finally, in Study 1b, we conduct supplemental analyses to determine whether performance feedback practices might contribute to changes in students' motivations at the beginning of the semester. Even though all students in a given course were required to submit mandatory weekly worksheets at the same time, scheduling differences across supplemental tutoring sections caused a delay in the provision of performance feedback for a subset of our sample. Due to these scheduling differences some of the students had received performance feedback at the time of data collection while others had not, which enabled us to examine the effects of receiving performance feedback for the first time on students' subsequent motivational changes (see Study 1b). We reasoned that the provision of performance feedback in these demanding courses may affect students' motivational trajectories (e.g., receiving performance feedback may contribute to an initial motivational decline), because their performance expectations may not yet be calibrated to the high demands and performance requirements in their study program (Metcalfe, 1998; Nowell & Alston, 2007).

Study 1a

Method

Participants and Procedure

The final sample in Study 1a included 1,004 participants (*n* = 318 female) from six cohorts of students enrolled in required math courses for beginning students in their respective study program at a German university. Each cohort consisted of students enrolled in the same course, at the same time, and in the same study program. The students were enrolled in physics (*n* = 366), math (*n* = 445), or math teacher education (*n* = 193), and two consecutive cohorts of students were recruited from each study program in the winter terms of the respective academic year (2017 and 2018). The majority of the students with valid demographic data were in their first year (90%), were born in Germany (90%), and indicated German as the language they most frequently speak at home (86%). Student-generated anonymized codes were used to link the longitudinal data. Twenty-seven students failed to provide a code, and seven students used systematic answer patterns such as straight-lining. These cases were not included in the analyses. If an individual participated in more than one course (e.g., courses in math and math teacher education), we analyzed data that were collected only in the study program in which the student was enrolled. Thus, we ensured that there was no overlap between course participants across courses and study programs. This procedure resulted in our final sample of 1,004 students (out of the initial 1,038).

Students participated voluntarily in the study and completed paper-and-pencil questionnaires at the beginning (Week 2, T1), midpoint (Week 8, T5), and end of the semester (Week 15, T6).[2] Data collections took place in regular math lectures. Nearly all students who were present on the day and time of data collection agreed to participate in the study (98%–100%), which allowed us to infer course attendance and attrition. All students were required to complete weekly math worksheets and to submit them in person in the lecture, and all students enrolled in a given math course were required to submit their worksheets at the same time. The students received performance feedback in separate tutoring sections, which were scheduled at different times. These tutoring sections were dedicated entirely to a discussion of the weekly math problems (the students were being shown step-by-step solutions on the whiteboard), and no new content was covered. The weekly worksheets were low-stakes assignments that the students had to pass to qualify for the exam, but students' level of performance on these assignments had no relevance for their final grade. Students in five of the six cohorts received scores as performance feedback and needed an overall score of 50% to qualify for the exam, whereas students in one cohort only received a pass/fail feedback and needed to pass 80% of the worksheets. The worksheets

[2] Week 1 is typically used for organizational questions, and data collection was not possible at this time. Students received their first course assignments in Week 2 and their first performance feedback in Week 3.

were highly demanding; almost no students were able to solve all problems in any given week. The students' achievement on the exam at the end of the semester determined their course grades.

Measures

The students responded to questions about their expectancy-value beliefs at all three time points in Study 1a (T1, T5, and T6) and rated their study program satisfaction at the end of the semester (T6).

Expectancy and Subjective Task Value Beliefs. The students' *expectancy* was measured with three items adapted from Eccles and Wigfield (1995) and Tanaka and Murayama (2014) (e.g., "Based on my experiences in this class, I think I will do well on the exam"). *Subjective task values* were assessed using scales adapted from Gaspard, Dicke, Flunger, Brisson, et al. (2015). Two-item scales were used for *intrinsic value* (e.g., "Doing the coursework and the assignments for this class is something I enjoy"), *utility value* (e.g., "Doing the coursework and the assignments for this class is useful for my future"), *psychological cost* (e.g., "Doing the coursework and the assignments for this class is stressful for me"), and *effort cost* (e.g., "Doing the coursework and the assignments for this class drains a lot of my energy"). All items were assessed on a 6-point scale ranging from 1 = *completely disagree* to 6 = *completely agree*. The internal consistencies of these constructs ranged from α = .67 to .92 across time points (see Table 1 as well as the online supplemental materials for the full list of items).

Study Program Satisfaction. Five items measuring study program satisfaction were adapted from Nauta (2007), Ditton (1998), and Westermann et al. (1996). Two items focused on students' certainty about their study choice (e.g., "I am certain that my study program is the right choice for me," from 1 = *very uncertain* to 6 = *very certain*); two items captured students' overall satisfaction (e.g., "In general, I am very satisfied with my study program," from 1 = *completely disagree* to 6 = *completely agree*); and one item captured dropout intentions ("I oftentimes think about dropping out of or switching my study program," reverse-scored, from 1 = *completely disagree* to 6 = *completely agree*). The internal consistency of the scale was very good (α = .89).

Course Dropout. Students' lack of attendance at the end of the semester (T6) was used as an indicator of course dropout in our analyses (39% of the sample). The majority of the students dropped out towards the midterm (24% non-attendance at both T5 and T6, and additional 15% non-attendance at T6). This high level of attrition is comparable to prior studies in gateway math courses (e.g., 38% in Rach & Heinze, 2017) and national dropout statistics for math-intensive study programs in Germany (45% in physics, 54% in math; Heublein & Schmelzer, 2018), and lack of course attendance has been shown to be a precursor to later academic difficulties (Schneider & Preckel, 2017).

Exam Performance. The students' scores on the final exam were obtained from the instructor of each math course. Written consent was obtained at T5 or T6, and 91% of all students who were present at these measurement points gave consent. Due to the high levels of course attrition, this percentage of informed consent corresponds to 54% of the total sample. The students' exam scores and course attrition were both included as outcome variables in subsequent analyses. The exam scores were converted into percentages and were z-standardized within each math course to account for instructor- and course-specific grading practices. One of the courses assigned only pass-fail grades (11% of the total sample), and 37 students (4% of the total sample) had submitted a written consent form but did not take the final exam; thus, no achievement data were available for these students.[3]

[3] We replicated our results (reported subsequently) using a dichotomous pass/fail variable for all students who had achievement data. Our findings were consistent regardless of whether we used this pass/fail variable or the exam scores. However, using the pass/fail variable resulted in somewhat weaker effect sizes, likely because this variable did not differentiate as well between different achievement levels.

Personal and Family Background Characteristics. The students reported their gender (34% female; 0 = *male*, 1 = *female*) and high school GPA at the beginning of the study. Students' high school GPA was recoded so that higher scores reflect higher achievement to facilitate the interpretation of results (M = 3.1, SD = 0.64, range from 1 to 4). The students' family background (SES) was coded based on student-reported parental occupations according to the German Classification of Occupations (KldB; Paulus & Matthes, 2013). This classification system differentiates between four job skill levels (1 = *requiring little or no education* to 4 = *requiring an advanced degree*). The majority of the students (61%) had at least one parent with the highest job level, and less than 1% of the students had parents whose occupation required little or no education. Accordingly, this variable was dichotomized into 0 = *low SES* (for job skill levels 1–3) versus 1 = *high SES* (for job skill level 4). The students' participation in preparatory math courses prior to enrollment (65% had participated) and dummy variables for each math course taught by a different instructor were included as covariates in all analyses. Both physics courses were taught by the same instructor; thus, only one dummy variable was included in this case.

Statistical Analyses

Preliminary analyses examined bivariate correlations and missing data patterns, and included confirmatory factor analyses (CFAs) testing measurement invariance across time points, between the different study programs, and students' gender, family background (SES), and participation in preparatory math courses. Latent change score analyses using M*plus* 8.3 explored short-term motivational changes (see McArdle, 2009). Missing data were handled with full information maximum likelihood estimation (FIML). We fit latent change models for each of the five expectancy-value constructs and a multivariate model including all five constructs (see Figure 1, McArdle, 2009). The latent change scores were modeled such that they assess changes in expectancy and task values from the beginning to the midpoint of the semester (ΔT5T1) and from the midpoint to the end of the semester (ΔT6T5). These change scores allowed us to describe potential discontinuities in the amount of change at the beginning versus towards the end of the semester. We modeled the predictive effects of the initial levels of motivation (T1) on the latent change scores (ΔT5T1), which is recommended when an “intervention” affecting the main variables of interest has taken place after the initial measurement occasion (McArdle, 2009). In the present study, the initial measurement (T1) took place before the students had received their first course assignment, whereas subsequent assessments (T5 and T6) took place after the students had engaged with demanding coursework. Furthermore, following recommendations by Grimm et al. (2012), we included predictive paths between the first (ΔT5T1) and the second (ΔT6T1) latent change scores; these paths model the potential predictive effects of early motivational changes on subsequent changes in students’ expectancies and task values.

For RQ#1, we modeled a multivariate latent change score model including the five expectancy-value constructs and examined means and variances of the latent change scores. We additionally estimated plausible values and corresponding confidence intervals for all latent change scores (Asparouhov & Muthén, 2010), which allowed us to identify students who experienced significant declines or increases in their expectancies and task values across the three measurement points. To answer RQ#2, we included students’ individual characteristics (gender, high school GPA, SES, participation in preparatory math courses) and math course/study program as predictors of their initial motivations and the latent change scores in the model in order to examine differences in students’ motivational trajectories as a function of preexisting differences in student characteristics. Finally, for RQ#3, we estimated separate latent change score models for each of the five expectancy-value constructs to examine the predictive effects of students’ initial motivations and the latent change scores on students’ end-of-term study program satisfaction, exam performance, and course dropout. A multivariate latent change model including the predictive effects of all five expectancy-value constructs and their latent change scores (i.e., 10 latent change scores in total) as predictors of students' academic success resulted in estimation problems and is not reported here. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and achievement, and a second set of analyses using Monte Carlo integration with 5,000 integration points focused on the prediction of course dropout.

Maximum likelihood estimation with robust standard errors (MLR) was used in all analyses. Model fit was evaluated based on the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). Good model fit is indicated by a CFI value of .95 or higher and RMSEA and SRMR values of .06 or lower, whereas acceptable fit is indicated by a CFI value of approximately .90 or higher and RMSEA and SRMR values of .08 or lower (Marsh et al., 2005). For model comparisons, a CFI difference between two models of less than .01 and an RMSEA difference of less than .015 generally indicate a negligible change in overall fit and support the more parsimonious model (Chen, 2007; Cheung & Rensvold, 2002). Analyses including course dropout (a dichotomous outcome variable) used MLR with the LINK = LOGIT option and Monte Carlo integration. For this analysis, model fit indices are not available.

Results

Preliminary Analyses

Descriptive statistics and bivariate correlations are shown in Table 1. All correlations between the expectancy-value constructs and hypothesized predictors and outcomes were in the expected direction. The means reported in Table 1 indicated that students' expectancy, intrinsic value, and utility value decreased over the three time points, on average, whereas the perceived psychological and effort cost increased. Attrition from the math courses (and thus from our study) is represented by the variable “course dropout” and was included as an outcome measure in our final analyses. As shown in Table 1, course dropout was linked to lower SES ($r = -.11$, $p = .002$), lower high school GPA ($r = -.39$, $p < .001$), lower likelihood of participation in preparatory math courses ($r = -.23$, $p < .001$), and less adaptive initial motivations. The students’ gender, SES, high school GPA, and participation in preparatory courses as well as instructor-/course-specific dummy variables were included as auxiliary or control variables in all subsequent models (Graham, 2003; Schafer & Graham, 2002).

Measurement Model and Invariance Analyses. Multigroup CFAs including expectancy, intrinsic and utility values, and psychological and effort costs confirmed the same factor structure for these constructs across students’ gender, family background (SES), and participation in preparatory math courses. Partial strong measurement invariance was supported across the different study programs (i.e., physics, math, and math teacher education) within each time point. Next, using the full sample, we were able to confirm strong measurement invariance across the three time points included in the study and for all five expectancy-value constructs (Widaman et al., 2010). Strong measurement invariance is a prerequisite for our latent change analyses and imposes equality constraints on the corresponding factor loadings and intercepts at each time point. Correlated residuals between the same indicator assessed at different time points were specified to account for indicator-specific covariances (Little, 2013). All invariance analyses are reported in the online supplemental materials.

Motivational Changes

To address our first research question (RQ#1) regarding the amount and shape of change in students’ course-specific motivations in gateway math courses over time, we tested a multivariate latent change score model including all five expectancy-value constructs. The model showed satisfactory fit to the data ($\chi^2 = 589.42$, $df = 382$, CFI = .986, RMSEA = .023, SRMR = .036). The model-estimated means of and variances in the expectancy-value constructs and latent change scores are shown in Table 2. On average, the students reported moderate to high levels of expectancy and subjective task values at the beginning of the semester (T1) and experienced a motivational decline from the beginning towards the midpoint of the semester (ΔT5T1; see Figure 2). This motivational decline was characterized by significant decreases in students' expectancy, intrinsic value, and utility value (ΔM = −0.36 to −0.30, ps < .001) and corresponding increases in perceived psychological and effort costs (ΔM = 0.40 and ΔM = 0.26, ps < .001; see Table 2). The amount of change in students' expectancy, intrinsic value, utility value and perceived psychological and effort cost from the beginning towards the midpoint (ΔT5T1) was comparable across the five different constructs. The only exception was a smaller increase in effort cost compared to the increase in psychological cost and the decrease in students' intrinsic value (ps ≤ .047; see the online supplemental materials for the full results of the Wald tests). The motivational changes from the midpoint towards the end of the semester in students' expectancy, intrinsic value, and utility value were significant (ΔT6T5: ΔM = −0.12 to −0.08, ps < .05) but substantially smaller than the initial motivational decline (ΔT5T1; ps ≤ .008). The amount of change in students' expectancy, intrinsic value, and utility value did not significantly differ from each other (ΔT6T5; ps ≥ .348).[4]

Analyses of plausible values for all latent change scores (Asparouhov & Muthén, 2010; see Table 2) allowed us to determine the percentage of students who experienced a significant decline or increase in their motivational beliefs (we generated 1,000 plausible values per person for each latent change score using Markov chain Monte Carlo Bayesian

[4] Two sets of supplemental analyses were conducted to describe the implications of missing data in both studies and to test the robustness of our findings (see supplemental materials). First, we replicated our analyses with and without the inclusion of students' individual and background characteristics as auxiliary variables. Second, we replicated our latent change score analyses using only the subsample of students who were present for the end-of-term data collection (T6).

estimation). Overall, between 72% and 78% of the students had negative change scores for expectancy, intrinsic value, and utility value, and between 66% and 75% had positive change scores for psychological and effort costs from the beginning towards the midpoint of the semester (ΔT5T1). The analysis of the plausible values and corresponding confidence intervals of the change scores allowed us to examine the proportion of significant changes: Between 10% and 21% of the students experienced significant declines in their expectancy, intrinsic value, and utility value during the first half of the semester, and hardly any students experienced a significant positive change (1%–4%). Analogously, a substantially higher percentage of students experienced significant increases (18%–19%) rather than decreases (3%–7%) in their psychological and effort costs in the first half of the semester. The amount of change in these beliefs from the middle towards the end of the semester was substantially smaller (ΔT6T5; only 2%–8% experienced a significant change from the midpoint towards the end of the semester). Importantly, there were significant interindividual differences in the amount of motivational change experienced by different students, as indicated by the significant variances in all latent change scores (see Table 2). We discuss possible factors that may contribute to these interindividual differences in the following section (corresponding to RQ#2).

Predictors of Motivational Changes

To answer our second research question (RQ#2), we included individual characteristics and instructor-/course-specific dummy variables as predictors of students' motivations in our latent change analysis. The model showed satisfactory fit to the data (χ^2 = 868.07, *df* = 525, CFI = .977, RMSEA = .026, SRMR = .031). As shown in Table 3, students' high school GPA was positively related to their initial levels of expectancy, intrinsic value, and utility value and negatively related to perceived cost (T1). In addition, students' high school GPA was a significant positive predictor of changes in their expectancy, intrinsic value, and utility value as well as a significant negative predictor of changes in their psychological cost from the beginning towards the midpoint of the semester (ΔT5T1). Students with higher GPAs not only started the semester with more positive motivational profiles but also experienced comparatively smaller motivational declines (and a smaller increase in psychological cost). However, the potential protective role of prior achievement against declines in desirable academic motivations (e.g., loss of interest) was limited to the beginning of the semester; students' high school GPA did not predict additional changes in expectancies and task values from the midpoint towards the end of the semester (ΔT6T5; see Table 3).

Controlling for differences in high school GPA and family background (see Table 3), we observed that, compared to male students, female students reported somewhat lower levels of expectancy and higher levels of psychological cost at the first measurement point (T1). Both male and female students experienced a motivational decline at the beginning of the semester (ΔT5T1); however, female students experienced a somewhat stronger motivational decline concerning their expectancy of success in the course and perceived utility value, as well as a greater increase in their perceived effort cost. No gender differences emerged for motivational changes from the midpoint towards the end of the semester (ΔT6T5). Students' SES and participation in preparatory math courses had no significant predictive effects on their motivational trajectories, with one exception: Compared to students from more advantageous family backgrounds, students from less advantageous family backgrounds experienced somewhat greater declines in intrinsic value from the midpoint towards the end of the semester (ΔT6T5; see Table 3).

These maladaptive motivational trajectories were universal across all math courses and study programs, but there were some course-specific differences in the percentage of students who experienced a significant negative motivational change. The results were most consistent for the observed declines in students' expectancy and intrinsic value and the observed increase in psychological cost across different courses and study programs (54%–92% of the students in a given course had negative change scores for expectancy and intrinsic value for ΔT5T1, and 61%–91% had a positive change score for psychological cost). Course-specific plausible values are reported in the online supplemental materials.

Motivational Changes as a Predictor of Students' Academic Success

To answer our third research question (RQ#3), we examined the predictive effects of students' initial motivations (T1) and motivational change scores (ΔT5T1 and ΔT6T5) as predictors of their end-of-term study program satisfaction, exam performance, and course dropout, controlling for students' gender, SES, high school GPA, and participation in preparatory math courses as well as instructor-/course-specific dummy variables. These analyses allowed us to determine the potential of short-term motivational changes to serve as early warning signs of later academic difficulties.

The latent change models for each of the five expectancy-value constructs, including all control variables as predictors and end-of-term study program satisfaction and exam performance as outcomes, showed satisfactory fit to the data (range of values: χ^2 = 178.79 to 272.27, *df* = 97 to 158, CFI = .957 to .982, RMSEA = .027 to .041, SRMR = .031 to .041). Residual covariances were allowed for items capturing similar content: the two items referencing students' study choice satisfaction and the two items referencing students' overall satisfaction with their study program. Standardized parameter estimates for the predictive effects of students' initial motivational beliefs and motivational changes are shown in Table 4 (see the online supplemental materials for the full results, including all covariates).

Students' initial levels of motivation (T1) significantly predicted their end-of-term study program satisfaction and exam performance in each of the five latent change models. Furthermore, controlling for differences in initial expectancy and task value beliefs and all remaining covariates, we observed that the latent change scores from the beginning towards the midpoint of the semester (ΔT5T1) significantly predicted students' end-of-term study program satisfaction and exam performance across all five models (see Table 4). The only exception was a nonsignificant effect of changes in utility value on exam performance (p = .055). Students who experienced stronger declines in expectancy, intrinsic value, and utility value and comparatively greater increases in psychological and effort costs at the beginning of the semester (ΔT5T1) were less satisfied with their study program at the end of the semester and performed worse on their final exam.

Additional changes in students' expectancy, intrinsic and utility values, and effort cost in the second half of the semester (ΔT6T5) had significant incremental predictive effects on their end-of-term study program satisfaction. Among the five expectancy-value constructs included in this study, only changes in students' expected success and intrinsic value towards the end of the semester (ΔT6T5) had significant incremental predictive effects on their end-of-term exam performance. This pattern of results suggests that the initial motivational decline experienced by students can serve as an early warning sign of later academic difficulties. Students' motivational beliefs were far less variable towards the end of the semester, and changes in these beliefs had negligible incremental predictive effects as a result, despite being more proximal in time to the final exam. Overall, the latent change models explained between 24% and 58% of the variance in students' study program satisfaction and between 31% and 41% of the variance in their exam performance (see Table 4).

Finally, an analogous set of latent change models was conducted for the prediction of students' course dropout. Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Accordingly, the analyses included latent change scores only from the beginning towards the midpoint of the semester (ΔT5T1). Students' initial levels of expectancy and intrinsic value (T1) had negative predictive effects and their initial perceived cost had positive predictive effects on students' end-of-term course dropout (see Table 4). The more positive students' motivational profiles were at the beginning of the semester (T1), the lower the likelihood of attrition from the course. In addition, the motivational decline in students' expectancy and intrinsic value towards the midterm (ΔT5T1) negatively predicted students' course dropout. Students who experienced smaller declines in their expectancy and intrinsic value (i.e., one standard deviation above the sample mean of the change score) were 19% to 20% less likely to drop out of their math course than students with mean-level motivational declines. Overall, the latent change models explained between 26% and 31% of the variance in course dropout.

Summary

The main results in Study 1a suggest that changes in students' motivational beliefs were most likely to occur in the first half of the semester and that these changes were generally maladaptive, i.e., they were characterized by declines in course-specific expectancy beliefs, intrinsic and utility values, and increases in psychological and effort costs (RQ#1). Some students experienced more maladaptive motivational changes than others as a function of their prior achievement and gender (RQ#2). Students' negative motivational changes at the beginning of the semester were a precursor to later academic difficulties, including lower levels of study program satisfaction, end-of-term achievement, and course attendance at the end of the semester (RQ#3).

Study 1b

Study 1b expanded upon Study 1a by conducting fine-grained analyses of students' motivational experiences during the very first weeks of the semester (T1–T4, corresponding to Weeks 2–5 of the semester). These analyses allow us to describe motivational changes shortly after the transition to higher education, to identify at what time point students' course-specific motivations typically begin to decline, and to determine whether situation-specific weekly shifts in students' motivations are related to their personal and background characteristics and are predictive of their end-of-term academic success. The research questions tested in Study 1b were analogous to those in Study 1a and focused on the amount and shape of change in students' motivations (RQ#1), the hypothesized predictors of these motivational changes (RQ#2), and the potential predictive effects of students' motivations on end-of-term academic outcomes (RQ#3). Unlike Study 1a, however, Study 1b focused on weekly motivational changes at the beginning of the semester and used motivational assessments that were not only course specific but also situation specific (i.e., focused on students' perceptions of the coursework that was covered that week). Furthermore, Study 1b allowed us to take advantage of scheduling differences in two of the math courses included in the study. Even though all students in these two courses had to submit their weekly worksheets in their math lecture at the same time, some students attended tutoring sections that were scheduled prior to rather than after their respective lectures. The students who attended a tutoring section prior to their lecture had already received feedback on their worksheet from the previous week at the time of data collection, whereas those whose section took place after the lecture had not. We compared the motivational profiles of these students in supplementary analyses.

Method

Participants and Procedure

Study 1b included five of the six cohorts from Study 1a (i.e., N = 773; one of the math cohorts did not participate in the weekly data collections). Study 1b was conducted at the same time and in the same lectures as Study 1a but included additional measurement points at the beginning of the semester. Specifically, in addition to the first data collection at the beginning of the semester (Week 2, T1), Study 1b included weekly surveys in three consecutive weeks (Weeks 3–5, T2–T4). Analogous to Study 1a, the data were collected in the same math lectures when the students were required to submit their solutions to the weekly math worksheets. As noted previously, the students had to pass these worksheets to qualify for their final exam but their course grade was determined solely by their performance on the final exam.

The potential effect of receiving delayed performance feedback on students' motivational trajectories was examined in supplemental analyses across two math courses in which the timing of receiving performance feedback varied between students (n = 296; one course in the math program and one in the math teacher education program). In these courses, approximately two-thirds of the students had received their weekly performance feedback at the time of data collection each week, whereas one-third of the students had not because their tutoring section was scheduled after the lecture in which we collected the data.

Measures

Weekly Expectancy and Subjective Task Value Beliefs. Students' expectancy-value beliefs were assessed each week using single items to reduce the survey length and, thus, the potential negative effects of survey fatigue due to repeated exposure to the same items over time (for a similar approach, see Martin et al., 2015; Tanaka & Murayama, 2014). The items focused on the content that was taught and practiced each week in the worksheets and were preceded by the following statement: "Think about the current worksheet you have turned in this week." Students' expectancy was assessed with the item "If the content of the current worksheet comes up on the exam: How well do you think will you perform on the exam?" (1 = *very poorly* to 6 = *very well*). Intrinsic and utility values and perceived psychological and effort costs were assessed with the following items: "Doing this week's assignments is something I enjoyed/…was generally useful/…was stressful for me/…drained a lot of my energy" (1 = *completely disagree* to 6 = *completely agree*).

End-of-Term Academic Outcomes. Analogous to Study 1a, students' study program satisfaction, exam performance, and course dropout were included as outcome variables. One set of analyses focused on the prediction of students' study program satisfaction and exam performance, and a separate set focused on potential course dropout.

Personal and Family Background Characteristics. Analogous to Study 1a, students' gender (36% female), SES (60% high SES), high school GPA (M = 3.1, SD = 0.65), and participation in preparatory math courses (63% participation) as well as instructor-/course-specific dummy variables were included as covariates in all models.

Delayed Performance Feedback. Of the students whose tutoring sections were scheduled either prior to or after their math lecture, 69% of the students received their first performance feedback between T1 and T2, whereas 31% received their first performance feedback between T2 and T3. The timing of students' weekly performance feedback was included as a binary predictor in the analyses (0 = *regular feedback*, 1 = *delayed feedback*). Students in both math courses received scores that reflected what proportion of the math problems were solved correctly on each worksheet.

Statistical Analyses

We used latent change models to examine potential changes in students' expectancy and task values during the first weeks after the transition to higher education in demanding, gateway math courses. Our use of weekly single-item indicators resulted in fully saturated measurement models. Plausible values were estimated for all latent change scores to determine the percentage of students experiencing significant motivational changes from week to week.

Results

Descriptive statistics and correlations between the situation-specific motivational variables across the four-week period are shown in Table 5 and were consistent with our expectations and with the correlational patterns reported in Study 1a. The means reported in Table 5 indicated that students' expectancy, intrinsic value, and utility value decreased sharply from T1 to T2 and remained relatively stable after this initial decline, whereas their psychological and effort costs showed a corresponding increase from T1 to T2 but fluctuated in the following weeks (from T2 through T4).

Motivational Changes

To answer our first research question (RQ#1) concerning the amount and shape of change in students' motivational beliefs, we fit a fully saturated latent change model for all expectancy-value constructs and their corresponding change scores. The model-estimated means of and variances in students' initial motivations and the latent change scores are shown in Table 6. These analyses revealed a "motivational shock" from T1 (Week 2) to T2 (Week 3) that was characterized by a rapid and significant decline in intrinsic and utility values ($\Delta M = -0.92$ and $\Delta M = -0.47$, *p*s < .001), a somewhat less pronounced but significant decline in students' expectancy ($\Delta M = -0.23$, $p < .001$), and a significant increase in psychological and effort costs ($\Delta M = 0.68$ and $\Delta M = 0.35$, *p*s < .001; see Figure 3). The mean-level changes were smaller in the following weeks ($\Delta M = -0.08$ to 0.06 for expectancy, intrinsic value, and utility value; $\Delta M = -0.39$ to 0.17 for psychological and effort costs). With the exception of effort cost, students' motivations stabilized at lower levels than their initial status (T1) by the end of the fourth weekly assessment (T4; *p*s < .001; see the online supplemental materials for the full results of the Wald tests). Additionally, the Wald tests indicated that the magnitude of the initial motivational shock varied between the expectancy-value constructs (ΔT2T1). Intrinsic value showed the most rapid decline compared to the other motivational facets (*p*s < .001), whereas the decline in students' expectancy was the smallest compared to the changes in the other motivational facets (*p*s ≤ .024). There was a greater increase in psychological cost than in effort cost ($p < .001$).

Analyses of plausible values for these latent change scores indicated that approximately 27% to 48% of all students experienced the initial motivational shock between T1 and T2 (see Table 6). Specifically, nearly half (48%) of all students experienced a sharp decline in their intrinsic value, and 27% to 41% of all students experienced significant declines in their expectancy of success and utility value and corresponding increases in their perceived cost. A substantially smaller proportion of students experienced positive changes in their motivations during this time (ΔT2T1, 7%–18%; see Table 6). This motivational shock coincided with the first time the students had received performance feedback on their weekly assignments. Analogous to Study 1a, we found significant interindividual differences in the amount of change in students' motivations across the four-week period, as indicated by the significant variances in all latent change scores (see Table 6).

Predictors of Motivational Changes

Next, we examined whether students' short-term motivational trajectories differed as a function of their personal and family background characteristics and respective math course (RQ#2). In general, the results were analogous to those in Study 1a. As shown in Table 7, students' high school GPA was a negative predictor of all three estimated latent change scores for students' expectancy (ΔT2T1, ΔT3T2, ΔT4T3) and a negative predictor of the first two latent change scores for intrinsic value (ΔT2T1, ΔT3T2). Thus, high school GPA served as a buffer against declines in these motivational beliefs across the four-week period. However, students' high school GPA was not consistently linked to changes in their utility value and perceived cost. Notably, and in contrast to Study 1a, students' high school GPA was a positive predictor of the initial increase in their psychological and effort costs; students with comparatively higher levels of prior achievement experienced stronger increases in their perceived cost in the first two weeks of the semester (ΔT2T1). This result suggests that relative to low-achieving students, high-achieving students may be more likely to increase their level of effort in the face of challenging coursework. We return to this point in the discussion.

Similar to Study 1a, we found small but significant gender differences in students' motivational trajectories in the first weeks of the semester (see Table 7). The initial decline in students' expectancy was more pronounced for female students than for male students, and there was a tendency towards a greater decline in female students' intrinsic value (ΔT2T1). Additionally, male students showed a greater decline in psychological and effort costs than female students after the initial motivational shock (ΔT3T2), which is a sign of potential "recovery" from the motivational shock that appears to be gender specific. Students' SES significantly predicted the initial decline in intrinsic and utility values (ΔT2T1) but was unrelated to further changes in their task values and expectancy across the four-week period. Students who had participated in optional preparatory math courses experienced a slightly greater recovery in their effort cost after the initial motivational shock (ΔT3T2), but they also experienced a greater increase in their psychological cost towards the end of the four-week period (ΔT4T3).

The identified motivational shock was observed in all math courses and study programs, but the amount of change varied across courses (see the course-specific plausible values in the online supplemental materials). The sharp decline in students' intrinsic value was universal across courses (ΔT2T1), whereas the onset of the decline in students' expectancy beliefs and utility value and the corresponding increase in their perceived cost varied across different courses.

Supplemental Analyses of Delayed Performance Feedback. Finally, supplemental analyses were conducted to examine whether the delay in receiving performance feedback each week had a significant effect on students' motivational trajectories. Receiving delayed performance feedback had a significant positive effect on changes in students' expectancy and a significant negative effect on change in students' psychological and effort costs (ΔT2T1; see Table 8). Students who received their first performance feedback on the mandatory worksheets a week later, and thus did not know their level of performance at the time of data collection (T2, which corresponded to Week 3), experienced a smaller decline in their expected success as well as smaller increases in their psychological and effort costs from T1 (Week 2) to T2 (Week 3) than students who had already received performance feedback. No significant differences in students' motivational trajectories between the two groups emerged for the remaining change scores (ΔT3T2, ΔT4T3). This finding suggests that receiving performance feedback appears to be a contributing factor to the motivational shock experienced in the first weeks of the semester.[5]

Motivational Changes as a Predictor of Students' Academic Success

Analogous to Study 1a and corresponding to our third research question (RQ#3), we modeled separate latent change models for the five expectancy-value constructs as predictors of students' end-of-term academic success. These models showed satisfactory fit to the data (range of values: χ^2 = 91.86 to 103.23, *df* = 51, CFI = .968 to .980, RMSEA = .032 to .036, SRMR = .033 to .038; see the online supplemental materials). Standardized parameter estimates for the predictive effects of the latent change scores (ΔT2T1, ΔT3T2, ΔT4T3) on students' end-of-term study program satisfaction and exam performance, controlling for students' background characteristics and math course, are shown in Table 9 (see the online supplemental materials for the full results, including all covariates).

Controlling for students' initial motivations (T1) and all hypothesized control variables, we observed that the motivational shock in the first weeks of the semester (ΔT2T1) emerged as a significant predictor of students' study program satisfaction and exam

[5] These two groups of students did not differ with regard to prior achievement (high school GPA: $M_{\text{regularFeedback}}$ = 3.22, $M_{\text{delayedFeedback}}$ = 3.23; $F(1, 264) = 0.012$, $p = .911$) and the number of points they received on their worksheet ($M_{\text{regularFeedback}}$ = 64.5, $M_{\text{delayedFeedback}}$ = 59.2; $F(1, 213) = 2.358$, $p = .126$).

performance across all five expectancy-value models. The only exception was a nonsignificant predictive effect of students' experienced change in intrinsic value on their exam performance (p = .056). Thus, the greater the motivational shock experienced by students in the very first weeks of the semester, the less satisfied they were with their study program, and the worse they performed on their final exam. In addition, students who experienced a greater recovery or smaller additional declines in their motivations after the initial shock (ΔT3T2) were comparatively more satisfied with their study program and had superior performance on the final exam. Only three of the tested predictive effects failed to reach significance (changes in intrinsic value failed to predict students' exam performance, p = .067, and changes in effort cost, p = .084, and psychological cost, p = .110, failed to predict their end-of-term study program satisfaction). Further motivational changes in the following week (ΔT4T3) had mostly nonsignificant incremental predictive effects on students' end-of-term study program satisfaction and exam performance across the five models. Overall, the latent change models explained between 20% and 41% of the variance in students' study program satisfaction and between 32% and 39% of the variance in their exam performance.

Finally, a set of latent change models for the prediction of students' course dropout was tested (see Table 9). Controlling for students' initial motivations and background characteristics, we observed that all three latent change scores for students' expectancy and intrinsic value (ΔT2T1, ΔT3T2, ΔT4T3) had negative predictive effects on students' course dropout. Students who experienced a smaller motivational shock in their expectancy and intrinsic value (ΔT2T1, i.e., one standard deviation above the sample mean), as well as a greater recovery in their expectancy and intrinsic value in the following weeks (ΔT3T2, ΔT4T3), were between 13% and 25% less likely to drop out of their math course. Across all four time points, changes in cost and utility value failed to predict course dropout, with only one exception (change in perceived utility at the end of the observation period, ΔT4T3, p =

.032). Overall, the latent change models explained between 24% and 30% of the variance in course dropout.

Summary

The analyses in Study 1b expand upon the evidence presented in Study 1a by demonstrating a “motivational shock” in the very first weeks of the semester that is characterized by a rapid decline in students’ academic motivations and, in particular, in their intrinsic interest (RQ#1). Although, on average, students’ motivational beliefs appear to stabilize during the following weeks—a potential sign of adaptation to the new learning environment and demands—students experience an overall motivational decline by the end of the observation period (T1–T4). The first provision of weekly performance feedback appeared to contribute to this motivational shock. Female students and students with comparatively lower prior performance experienced more negative motivational trajectories (RQ#2). The observed motivational shock in the very first weeks of the semester was predictive of end-of-term academic outcomes and can thus be interpreted as an early warning sign of later academic difficulties (RQ#3).

General Discussion

Our research focused on the development of students’ expectancy and subjective task values shortly after the transition to higher education in math-intensive study programs and examined interindividual differences in students’ motivational trajectories and the predictive effects of these motivational changes on students’ academic success. Our findings in both studies underscore the importance of examining short-term changes in students’ expectancy and subjective task values after the transition to higher education. First, whereas Study 1a corroborates prior research that has documented a motivational decline over the course of a semester (Kosovich et al., 2017; Zusho et al., 2003), Study 1b is the first to document a motivational shock in the very first weeks of the semester in demanding gateway math courses. In addition, we found motivational declines in all math courses, indicating that these declines were fairly generalizable across the different math-intensive study programs in our study. Second, we found that students’ situated expectancy and task value beliefs did not follow the same trajectory across the first weeks of the semester in Study 1b, which underscores the importance of considering different facets of SEVT to better understand students’ educational experiences. Third, the identified motivational declines across both studies significantly predicted students’ end-of-term study program satisfaction, exam performance, and course dropout. Thus, our data suggest that short-term motivational declines function as early warning signs of academic difficulties and dropout tendencies. Finally, our findings have implications for the design of motivational interventions and suggest that construct- and context-specific interventions are needed in the very first weeks of the semester to support students’ academic success and to potentially prevent dropout from math-intensive study programs. We discuss our main findings in detail in the following sections.

Motivational Changes: Why Short-Term Assessments Matter

Consistent with prior evidence (Kosovich et al., 2017; Perez et al., 2014; Zusho et al., 2003), Study 1a revealed a motivational decline over one semester after the transition to higher education. Whereas prior research had mostly studied composite scores of students’ task value (Dresel & Grassinger, 2013; Zusho et al., 2003) or focused on single task value facets (e.g., utility value; Kosovich et al., 2017), we examined the trajectories of different facets of the expectancy-value framework over one semester in gateway math courses. We found that students’ expectancy, intrinsic value, and utility value decreased and that their perceived psychological and effort costs increased across the semester. This motivational decline was mostly limited to the first half of the semester, which is in line with prior evidence in introductory college courses that has documented greater declines in students’ motivations in the first half than in the second half of a semester (Kosovich et al., 2017; Zusho et al., 2003).

Importantly, our analyses in Study 1b extend prior research by documenting a motivational shock in the very first weeks of the semester that is characterized by a sharp decline in students' intrinsic and utility values, a comparatively smaller decline in their expected success, and an increase in their perceived psychological and effort costs. Study 1a indicated a much smaller motivational decline across the first half of the semester, compared to the sizeable motivational shock in the first weeks of the semester observed in Study 1b. This discrepancy suggests that students partially recovered from the initial motivational shock by mid-semester. Thus, students' motivations do not appear to show a steady decline over one semester but, instead, change in a nonlinear fashion shortly after the transition to higher education. This developmental pattern of students' expectancy-value beliefs is consistent with the assumption of a period of adaptation to the new learning environment (Eccles & Midgley, 1989).

In addition, our results suggest that different expectancy-value beliefs do not change at the same rate after the transition to higher education. Even though the trajectories of students' course-specific motivations in Study 1a were similar for the five expectancy-value constructs, we found that students' situated expectancies and task values did not follow the same trajectory in Study 1b. The initial motivational shock was particularly pronounced for students' subjective task values, which appear to be more sensitive to the new educational context in math-intensive study programs than students' expectancy. In addition, students' initial task values were somewhat higher than their initial levels of expectancy (with the exception of psychological cost, which was comparable) so that there was greater potential for change in students' task values than in expectancy.

The transition from school math to learning university-level math might be a contributing factor to the strong declines in students' intrinsic and utility values and the corresponding increase in their perceived cost. This transition is accompanied by a shift in the nature of math content from applied math in school to math as a scientific discipline (Gueudet, 2008). Thus, students might have unrealistic expectations of the math content and day-to-day coursework in university math courses, which might explain the rapid changes in their subjective task values.

Relatedly, our finding that students' expectancy beliefs changed at a smaller rate after the transition to higher education than their task values differs from prior studies, which found greater declines in students' expectancy or competence-related beliefs than in their task values (Kosovich et al., 2017; Perez et al., 2014; Perez et al., 2019; but see Zusho et al., 2003). Context-specific differences in the type of performance evaluations and exams may contribute to these discrepancies (Church et al., 2001). Prior studies in the US have shown that students' exam performance during the semester significantly predicts declines in competence-related beliefs (Kosovich et al., 2017; Perez et al., 2014). In contrast, German students usually do not take graded exams during the semester. In our study, as is typical for German universities, students had to pass weekly worksheets to quality for the final exam, but they were allowed to collaborate with other students and their level of performance on the worksheets had no bearing on their final grade. The lack of high-stakes exams during the semester may thus explain the smaller decline in expectancy than in task values in Study 1b.

Furthermore, students' psychological cost showed a larger increase than their effort cost across both studies, which deviates from previous research in which the opposite pattern was found (Perez et al., 2014; Perez et al., 2019; Robinson et al., 2019). However, the students in our study reported high effort cost already at the beginning of the semester (compared to moderate levels of psychological cost), likely due to preconceptions about the high workload in math-intensive study programs or their experiences with the coursework in preparatory math courses. Thus, even though effort cost did not change as much, it remained at a relatively high level throughout the study. The stronger increase in students' psychological rather than effort cost in our study may at least in part be due to assessment differences relative to prior research. We assessed psychological cost using situation-specific measures (e.g., feeling stressed or nervous while working on the weekly assignments), whereas the assessments used in prior research have often referenced relatively stable and global attitudes towards failure or declines in students' self-esteem (e.g., Perez et al., 2014).

Predictors of Motivational Changes

Across both studies, we found relatively small but notable differences in students' motivational trajectories as a function of their gender, SES, prior achievement (i.e., high school GPA), and participation in preparatory math courses. Notably, however, our sample consisted primarily of male, high-achieving students from high-SES backgrounds, which may diminish the predictive power of these variables. Nevertheless, our findings indicate that female students and students with comparatively lower high school GPAs are at risk of experiencing more negative motivational trajectories across the transition to higher education. These results are consistent with prior evidence showing that prior achievement serves as a buffer against later motivational declines (Robinson et al., 2019; Sonnert et al., 2015). Unexpectedly, we found that students' psychological and effort costs in Study 1b increased more for students with comparatively higher high school GPAs. This result suggests that high- and low-achieving students may show different processes of adaptation to the high demands of their math-intensive study programs. High-achieving students may be more likely to increase their level of effort in the face of challenge and negative feedback, thus leading to higher levels of perceived cost, whereas low-achieving students may instead adjust their levels of aspiration and expected success (Vancouver et al., 2008; Vancouver et al., 2002).

Even though the observed gender differences in students' motivational trajectories were relatively small, they consistently favored male students over female students, which is in line with prior evidence (Robinson et al., 2019; Sonnert et al., 2015; Watt, 2004). The identified gender differences were mostly limited to students' expectancy and perceived cost, suggesting that gender stereotypes may play a role in the development of female students' expectancy and cost perceptions (Ertl et al., 2017).

Notably, motivational declines were observed in all math courses, which points to a relatively generalizable process of adjusting to the instructional climate of math-intensive study programs in our sample (e.g., high workload, instructors' fixed ability mindsets, grading on a curve; see Seymour & Hewitt, 1997; Sonnert et al., 2015). However, course-specific differences in students' motivational trajectories emerged as well; whereas the sharp decline in students' intrinsic value shortly after the transition to college was observed in all courses, students' expectancy, utility value, and perceived cost changed rapidly in some courses but more gradually in others. Course-specific differences in the math content covered each week or different instructional practices may be a contributing factor to these discrepancies.

Finally, the supplemental analyses in Study 1b showed that not only the exposure to challenging content but also receiving performance feedback is a contributing factor to the students' motivational shock in the first weeks of the semester. Accordingly, the provision of motivationally supportive performance feedback might be a promising avenue to decrease the motivational shock experienced by students at the beginning of the semester. Such feedback practices include, for instance, formative feedback practices that instruct students on how to improve their study strategies and performance as well as instructional adaptations that take into account the needs of individual students (Fong et al., 2019; Jonsson, 2013; Shute, 2008).

Motivational Changes as a Predictor of Students' Academic Success

Our analyses across both studies revealed that short-term changes in students' expectancy and subjective task values—including the motivational shock observed in Study 1b—were predictive of their end-of-term exam performance, study program satisfaction, and course dropout. Thus, not only are the motivational declines shortly after the transition to higher education a sign of students' adaptation to the new educational context and demands of math-intensive study programs, but they also serve as predictors of students' academic success at the end of their first semester in college (see also Dresel & Grassinger, 2013; Kosovich et al., 2017). Our results thus point to the potential of early motivational interventions to reduce student dropout and improve students' well-being and performance in math-intensive study programs. Maladaptive motivational changes were most likely to occur in the first weeks of the semester; thus, motivational interventions should be administered in the early stages of students' college careers (Canning et al., 2018; Hulleman et al., 2017). For instance, Canning et al. (2018) found that writing about the perceived usefulness of the course content improved students' final exam grades in an introductory biology course and increased students' likelihood of enrolling in a subsequent course. Notably, students who were most at risk for low academic achievement (i.e., students with a history of poor performance) benefitted the most if the intervention was administered in the first weeks of the semester. Our study suggests that students' motivations are most likely to decline during this time.

Furthermore, students' task values were more vulnerable to motivational declines than students' expectancy in the first weeks of the semester. Therefore, interventions targeting students' valuing of academic content are needed to support students' academic success in math-intensive programs. Emerging evidence suggests that motivational interventions based on Eccles et al.'s SEVT can benefit not only the values that are explicitly targeted in these interventions (e.g., utility and intrinsic values) but also nontargeted facets of the expectancy-value framework (Hulleman et al., 2017; Rosenzweig et al., 2020). For instance, Rosenzweig et al. (2020) found that a cost reduction and a utility value intervention improved students' exam scores in a physics course in college by boosting initially lower-performing students' competence-related beliefs. Implementing motivational interventions shortly after the transition to higher education that target students' subjective task values may thus be a fruitful approach to buffering students from motivational declines and thus increasing their academic success and retention in math-intensive study programs.

Limitations and Directions for Future Research

Our research is the first to examine short-term changes in students' expectancy and subjective task values immediately after the transition to higher education in math-intensive study programs and to document a motivational shock experienced by students in the first weeks of college. However, several limitations must be considered in the interpretation of our findings. First, our research focused specifically on math courses at the beginning of higher education, as such courses typically function as gatekeepers in the STEM domain (Seymour & Hewitt, 1997). Therefore, the generalizability of the identified motivational shock to other domains remains unclear. Research in the school context has shown greater declines in students' motivations in math courses than in English courses over one academic term (Mac Iver et al., 1991). It is thus possible that the motivational shock is at least partially inherent to the context of (university) math, and to a lesser extent linked to a general process of adapting to higher education. Further research in other contexts and study domains is therefore needed.

Second, our study focused on the short-term development of students' expectancy and task values since academic difficulties in gateway math courses can stall students' progression towards a STEM degree (Seymour & Hewitt, 1997), and the majority of students who drop out of math-intensive study programs do so within their first year in college

(Heublein et al., 2017). However, analyses beyond this critical period are needed to examine the potential long-term consequences of the motivational shock for students' degree completion, overall GPA, and study program dropout.

Third, 39% of the students were no longer attending their math course by the end of the semester, which we defined as course dropout. However, even though this high level of attrition is similar to the dropout rates reported in other studies in gateway math courses (e.g., 38%; Rach & Heinze, 2017), we were unable to unambiguously determine the reason why these students were not present in class. Monitoring students' behaviors outside of class would have been necessary to answer this question.

Fourth, even though our study is one of the first to assess short-term changes in different facets of the expectancy-value framework, we did not include students' attainment value and opportunity cost in our study due to length constraints and concerns about survey fatigue. Relatedly, our reliance on two-item scales in Study 1a and single-items in Study 1b is a limitation because we used a limited number of indicators to describe different facets of the expectancy-value framework. In recent years, broader measures tapping different subfacets of the expectancy-value framework have been developed (e.g., utility for daily life vs. utility for job; Gaspard, Dicke, Flunger, Schreier, et al., 2015). Examining a broader array of constructs and corresponding short-term changes may provide further insight into which facets may be particularly malleable after the transition to a new educational context and could thus be targeted in educational interventions.

Finally, the sample of our research was relatively homogeneous in terms of the students' gender, family background, and prior achievement, and the covariates included in our study were insufficient to explain the motivational shock found in our study. More work is needed to better understand which factors contribute to students' recovery from the initial motivational shock and to support students who are most at risk of negative motivational trajectories after the transition to higher education. Such factors might include students' mindset beliefs about the fixedness or malleability of their abilities or students' perceptions of their instructors' mindset beliefs (Dweck & Yeager, 2019; Muenks et al., 2020). Relatedly, our latent change score analyses were limited to average trajectories of students' expectancy-value beliefs across the first weeks and first semester at university. Other methodological approaches such as growth mixture modeling (Muthén, 2004) would be suitable to explore if there are groups of students with qualitatively different trajectories across the first semester in math-intensive study programs and may be able to identify specific at-risk-groups that could benefit from early interventions (e.g., Gaspard et al., 2020).

Conclusion

Understanding the reasons for students' decisions to persist in or drop out of math-intensive study programs is an important objective to increase the involvement of talented youth in the STEM domain. Our study examined the developmental trajectories of students' expectancy-value beliefs shortly after the transition to higher education and investigated the role of short-term motivational changes as potential warning signs of later academic difficulties in gatekeeper math courses. Our analyses suggest that students experienced a motivational shock immediately after the transition to higher education that was in part linked to their first performance feedback. Our analyses identified interindividual differences in students' motivational trajectories as a function of their gender, prior achievement, SES, and their respective math course and study program. However, a motivational shock was observed in all courses, suggesting that many students were experiencing a period of adaptation to the high demands and the instructional climate in the math-intensive study programs included in our study. The motivational shock served as a risk factor for later academic difficulties and course dropout at the end of the first semester in college. Thus, analyses of motivational trajectories should consider not only the long-term but also the short-term changes in students' motivations to better understand their decisions to persist in or drop out of math-intensive programs. Short-term motivational changes are not only a concomitant of students' adaptation to a novel and challenging learning environment but also a predictor of their subsequent performance, persistence, and well-being in the STEM domain.

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Table 1

Descriptive Statistics and Observed Bivariate Correlations in Study 1a

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1. Female	—																					
2. SES	.05	—																				
3. High school GPA	.05	.19**	—																			
4. Preparatory course	.03	.11**	.21**	—																		
5. Expectancy T1	−.18**	.04	.16**	−.03	—																	
6. Intrinsic value T1	−.03	.04	.20**	.11**	.43**	—																
7. Utility value T1	−.02	.01	.06	.08*	.31**	.39**	—															
8. Psych. cost T1	.16**	−.08*	−.09**	−.07*	−.51**	−.35**	−.22**	—														
9. Effort cost T1	.05	−.03	−.03	.01	−.44**	−.18**	−.13**	.62**	—													
10. Expectancy T5	−.20**	.03	.23**	.00	.66**	.31**	.17**	−.42**	−.38**	—												
11. Intrinsic value T5	−.04	.03	.25**	.06	.33**	.49**	.21**	−.27**	−.13**	.53**	—											
12. Utility value T5	−.05	.03	.12**	.03	.27**	.28**	.55**	−.20**	−.15**	.34**	.45**	—										
13. Psych. cost T5	.14**	−.06	−.20**	−.07	−.33**	−.21**	−.06	.58**	.42**	−.49**	−.34**	−.13**	—									
14. Effort cost T5	.08*	−.03	−.11**	−.02	−.31**	−.12**	−.01	.41**	.53**	−.41**	−.15**	−.05	.68**	—								
15. Expectancy T6	−.18**	−.02	.18**	−.04	.61**	.30**	.21**	−.38**	−.36**	.78**	.39**	.27**	−.44**	−.38**	—							
16. Intrinsic value T6	−.03	.11*	.15**	.05	.26**	.41**	.21**	−.26**	−.13**	.43**	.64**	.34**	−.31**	−.17**	.50**	—						
17. Utility T6	−.04	.08	.18**	.05	.25**	.26**	.51**	−.24**	−.16**	.34**	.34**	.67**	−.22**	−.10*	.30**	.45**	—					
18. Psych. cost T6	.12**	−.10*	−.12**	−.05	−.36**	−.27**	−.12**	.58**	.38**	−.46**	−.32**	−.12*	.68**	.52**	−.49**	−.32**	−.18**	—				
19. Effort cost T6	.04	−.03	−.07	.03	−.32**	−.16**	−.05	.41**	.50**	−.42**	−.16**	−.06	.48**	.69**	−.40**	−.18**	−.06	.64**	—			
20. Study satisfaction T6	−.13**	.01	.20**	.04	.45**	.41**	.25**	−.41**	−.30**	.54**	.48**	.39**	−.45**	−.28**	.57**	.56**	.41**	−.42**	−.28**	—		
21. Exam performance	−.12*	.07	.41**	.03	.27**	.17**	.17**	−.25**	−.34**	.39**	.21**	.23**	−.33**	−.32**	.42**	.24**	.22**	−.30**	−.36**	.33**	—	
22. Course dropout	−.04	−.11**	−.39**	−.23**	−.14**	−.17**	.00	.15**	.07*	−.21**	−.26**	−.09*	.16**	.07	[a]	[a]	[a]	[a]	[a]	[a]	[a]	—
M	.34	.61	3.13	.65	3.71	4.74	4.54	3.13	4.31	3.43	4.43	4.29	3.48	4.54	3.44	4.47	4.26	3.43	4.47	4.43	.00	.39
SD	.48	.49	.64	.48	.85	.81	.99	1.24	1.09	.92	0.91	1.06	1.19	1.03	1.00	.90	1.00	1.23	1.00	.93	.99	.49
N	928	811	896	794	887	899	894	899	899	693	695	693	694	695	517	520	518	520	520	520	393	1004
Skewness			−.45		.03	−.75	−.82	.35	−.44	−.14	−.70	−.65	.10	−.73	−.16	−.89	−.57	.28	−.48	−.84	−.05	
Kurtosis			−.64		.51	1.13	.79	−.57	−.05	.33	.84	.40	−.49	.36	.15	1.07	.35	−.47	−.09	.83	−.54	
Cronbach's α					.89	.79	.67	.81	.89	.92	.83	.74	.79	.91	.92	.84	.68	.83	.90	.89		

Note. N = 1,004. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15). Psych. cost = psychological cost.

[a] Course dropout implies that the students were not present at the end-of-semester data collection and no performance data was available, so that correlations could not be computed.

* p < .05. ** p < .01.

Table 2

Latent Means and Variances of Initial Motivations and Latent Change Scores and Amount of Students Experiencing Significant Changes in Their Motivations in Study 1a

Variable	T1		ΔT5T1		ΔT6T5		ΔT5T1		ΔT6T5	
	M	σ^2	*M*	σ^2	*M*	σ^2	Decrease	Increase	Decrease	Increase
Expectancy	3.74	0.69^{***}	-0.34^{***}	0.45^{***}	-0.09^{**}	0.30^{***}	21% (78%)	4% (22%)	8% (61%)	3% (39%)
Intrinsic value	4.57	0.54^{***}	-0.36^{***}	0.52^{***}	-0.08^{*}	0.33^{***}	17% (77%)	1% (23%)	6% (56%)	2% (44%)
Utility value	4.62	0.88^{***}	-0.30^{***}	0.67^{***}	-0.12^{**}	0.39^{***}	10% (72%)	2% (28%)	5% (60%)	2% (39%)
Psych. cost	2.75	1.01^{***}	0.40^{***}	0.69^{***}	0.01	0.44^{***}	3% (25%)	19% (75%)	4% (50%)	5% (50%)
Effort cost	4.33	1.02^{***}	0.26^{***}	0.83^{***}	−0.03	0.45^{***}	7% (34%)	18% (66%)	6% (55%)	5% (45%)

Note. Plausible values were generated for each latent change score using Bayesian estimation to determine the amount of students experiencing significant changes in their expectancy-value beliefs. The amount of students with negative and positive latent change scores is shown in parentheses. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15). Psych. cost = psychological cost.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 3

Standardized Path Coefficients for Predictors of Initial Motivations and Motivational Changes in Study 1a

Predictors	T1	ΔT5T1	ΔT6T5
Expectancy			
Female	$-.19^{***}$	$-.18^{***}$	$-.02$
SES	.01	.02	$-.04$
High school GPA	$.24^{***}$	$.23^{***}$	.11
Preparatory course	$-.06$	.01	$-.04$
Math1	$-.11^{**}$	$.17^{***}$	$-.23^{***}$
Math2	$-.13^{**}$	$-.05$	$-.14^{*}$
Teacher1	$-.07^{*}$	$.16^{***}$	.00
Teacher2	$-.04$	$.18^{***}$	$-.06$
Intrinsic value			
Female	$-.03$	$-.03$	.01
SES	$-.01$	.01	$.13^{*}$
High school GPA	$.25^{***}$	$.16^{**}$	$-.01$
Preparatory course	$.08^{*}$	$-.03$	.02
Math1	$-.15^{***}$	$.29^{***}$	$-.24^{**}$
Math2	$-.17^{***}$	.03	$-.17^{*}$
Teacher1	$-.19^{***}$	$.12^{*}$	.05
Teacher2	$-.11^{*}$	$.18^{***}$	$-.13^{\dagger}$
Utility value			
Female	$-.02$	$-.10^{*}$	.01
SES	$-.02$	.05	.07
High school GPA	$.11^{**}$	$.10^{*}$	.13
Preparatory course	$.08^{\dagger}$	$-.07$	$-.01$
Math1	$-.25^{***}$	$.09^{\dagger}$	$-.24^{***}$
Math2	$-.35^{***}$	.00	$-.25^{**}$
Teacher1	$-.23^{***}$	.00	$-.07$
Teacher2	$-.31^{***}$	$.24^{***}$	$-.29^{**}$
Psychological cost			
Female	$.16^{***}$	$.08^{\dagger}$	$-.09$
SES	$-.06^{\dagger}$	.01	$-.04$
High school GPA	$-.12^{**}$	$-.17^{***}$	.04
Preparatory course	$-.04$	$-.01$	.05
Math1	$.16^{***}$	$-.17^{***}$	.07
Math2	$.26^{***}$	$-.12^{*}$	$-.02$
Teacher1	$.16^{***}$	$-.17^{***}$	.00
Teacher2	$.13^{***}$	$-.18^{***}$	.03
Effort cost			
Female	.05	$.08^{*}$	$-.10^{\dagger}$
SES	$-.03$	.00	.02
High school GPA	$-.09^{*}$	$-.06$	$-.05$
Preparatory course	.02	$-.02$	$.10^{\dagger}$
Math1	$.20^{***}$	$-.12^{**}$	$-.04$
Math2	$.24^{***}$	$-.17^{**}$	$-.10^{\dagger}$
Teacher1	$.10^{**}$	$-.21^{***}$	$-.10$
Teacher2	$.12^{**}$	$-.20^{***}$	$-.05$

Note. Predictive effects of levels of motivation on motivational changes (T1 → ΔT5T1, T5 → ΔT6T5) as well as predictive effects of early motivational changes on subsequent changes (ΔT5T1 → ΔT6T5) are not shown. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15). Math1, Math2, Teacher1 and Teacher2 = dummy variables for the respective math courses and study programs.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 4

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in Study 1a

Model and predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Covariates	[a]	[a]	[a]	
R^2	.12	.28	.26	
Expectancy				
T1	$.62^{***}$	$.31^{***}$	$-.17^{***}$	0.84
ΔT5T1	$.39^{***}$	$.27^{***}$	$-.22^{***}$	0.81
ΔT6T5	$.18^{**}$	$.14^{*}$	[b]	
R^2	.51	.41	.31	
Intrinsic value				
T1	$.70^{***}$	$.24^{***}$	$-.18^{***}$	0.84
ΔT5T1	$.48^{***}$	$.20^{**}$	$-.23^{**}$	0.80
ΔT6T5	$.31^{***}$	$.16^{*}$	[b]	
R^2	.58	.36	.31	
Utility value				
T1	$.49^{***}$	$.18^{**}$	.04	1.04
ΔT5T1	$.47^{***}$	$.16^{\dagger}$	−.07	0.93
ΔT6T5	$.26^{*}$	.02	[b]	
R^2	.35	.31	.26	
Psychological cost				
T1	$-.58^{***}$	$-.35^{***}$	$.11^{*}$	1.12
ΔT5T1	$-.35^{***}$	$-.23^{**}$	.04	1.04
ΔT6T5	$-.11^{\dagger}$	−.03	[b]	
R^2	.36	.36	.27	
Effort cost				
T1	$-.42^{***}$	$-.39^{***}$	$.10^{*}$	1.10
ΔT5T1	$-.22^{**}$	$-.17^{**}$	.03	1.03
ΔT6T5	$-.14^{*}$	−.09	[b]	
R^2	.24	.38	.27	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set focused on the prediction of course dropout. *OR* = odds ratio. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Covariates were students' gender, SES, high school GPA, participation in preparatory courses, and dummies for the math courses. See the online supplemental material for the full results, including all covariates.

[b] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). The analyses therefore included only the latent change score from the beginning towards the midpoint of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 5

Descriptive Statistics and Observed Bivariate Correlations in Study 1b

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Expectancy T1	—																			
2. Intrinsic value T1	.44**	—																		
3. Utility value T1	.27**	.34**	—																	
4. Psych. cost T1	−.49**	−.39**	−.23**	—																
5. Effort cost T1	−.43**	−.25**	−.07	.59**	—															
6. Expectancy T2	.50**	.24**	.05	−.27**	−.23**	—														
7. Intrinsic value T2	.22**	.31**	.05	−.13*	−.07	.48**	—													
8. Utility value T2	.16**	.23**	.26**	−.10*	.01	.31**	.53**	—												
9. Psych. cost T2	−.24**	−.12**	.02	.31**	.29**	−.43**	−.30**	−.12**	—											
10. Effort cost T2	−.21**	−.05	.12**	.20**	.33**	−.42**	−.21**	−.03	.74**	—										
11. Expectancy T3	.56**	.28**	.14**	−.35**	−.34**	.55**	.24**	.13**	−.28**	−.27**	—									
12. Intrinsic value T3	.39**	.41**	.18**	−.26**	−.20**	.33**	.40**	.28**	−.18**	−.11*	.54**	—								
13. Utility value T3	.32**	.31**	.31**	−.18**	−.11**	.19**	.22**	.42**	−.08	.01	.34**	.58**	—							
14. Psych. cost T3	−.40**	−.27**	−.09*	.46**	.45**	−.34**	−.16**	−.08	.47**	.39**	−.53**	−.38**	−.22**	—						
15. Effort cost T3	−.33**	−.19**	−.02	.36**	.46**	−.31**	−.09*	−.02	.40**	.46**	−.45**	−.25**	−.07	.77**	—					
16. Expectancy T4	.48**	.26**	.07	−.35**	−.37**	.52**	.27**	.19**	−.27**	−.25**	.57**	.35**	.26**	−.36**	−.31**	—				
17. Intrinsic value T4	.28**	.33**	.05	−.22**	−.14**	.34**	.48**	.34**	−.14**	−.06	.30**	.45**	.29**	−.14**	.00	.56**	—			
18. Utility value T4	.19**	.33**	.29**	−.18**	−.07	.23**	.29**	.47**	−.03	.05	.28**	.38**	.52**	−.12**	−.01	.39**	.56**	—		
19. Psych. cost T4	−.30**	−.14**	.03	.34**	.34**	−.28**	−.15**	−.10*	.46**	.34**	−.27**	−.19**	−.12**	.48**	.40**	−.43**	−.34**	−.16**	—	
20. Effort cost T4	−.25**	−.08	.07	.26**	.41**	−.26**	−.06	.00	.39**	.40**	−.25**	−.14**	−.04	.43**	.46**	−.36**	−.13**	.01	.73**	—
M	3.73	4.57	4.62	3.49	4.31	3.56	3.70	4.17	4.13	4.62	3.60	3.72	4.13	3.92	4.25	3.55	3.71	4.09	4.11	4.34
SD	.90	.87	1.13	1.35	1.15	1.08	1.20	1.07	1.33	1.24	1.10	1.10	1.03	1.39	1.25	1.03	1.14	1.03	1.25	1.18
N	684	692	683	691	693	617	619	615	621	620	582	585	583	584	585	557	557	554	553	555
Skewness	−.16	−.44	−.88	.11	−.37	−.11	−.38	−.70	−.43	−.80	−.39	−.56	−.57	−.20	−.36	−.30	−.47	−.71	−.27	−.52
Kurtosis	.29	.39	.74	−.70	−.34	−.19	−.34	.42	−.61	.00	.05	.02	.34	−.85	−.54	−.05	−.16	.61	−.64	−.24

Note. N = 773. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. Psych. cost = psychological cost.

* p < .05. ** p < .01.

Table 6

Latent Means and Variances of Initial Motivations and Latent Change Scores and Amount of Students Experiencing Significant Changes in Their Motivations in Study 1b

Variable	T1		ΔT2T1		ΔT3T2		ΔT4T3		ΔT2T1		ΔT3T2		ΔT4T3	
	M	σ^2	*M*	σ^2	*M*	σ^2	*M*	σ^2	Decr.	Incr.	Decr.	Incr.	Decr.	Incr.
Expectancy	3.73	0.83***	−0.23***	0.99***	0.06	1.06***	−0.08†	0.97***	27% (60%)	16% (36%)	18% (45%)	21% (51%)	20% (52%)	13% (44%)
Intrinsic value	4.56	0.77***	−0.92***	1.52***	0.03	1.58***	−0.03	1.37***	48% (83%)	7% (14%)	21% (49%)	21% (48%)	20% (51%)	18% (46%)
Utility value	4.62	1.27***	−0.47***	1.81***	−0.03	1.28***	−0.05	1.03***	36% (67%)	16% (29%)	20% (52%)	19% (46%)	18% (51%)	15% (46%)
Psych. cost	3.49	1.82***	0.68***	2.49***	−0.22***	2.01***	0.17**	1.88***	15% (28%)	41% (69%)	28% (55%)	19% (42%)	16% (45%)	24% (52%)
Effort cost	4.30	1.33***	0.35***	1.85***	−0.39***	1.71***	0.07	1.63***	18% (37%)	34% (60%)	32% (65%)	15% (34%)	17% (46%)	23% (51%)

Note. Plausible values were generated for each latent change score using Bayesian estimation to determine the amount of students experiencing significant changes in their expectancy-value beliefs. The amount of students with negative and positive latent change scores is shown in parentheses. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. Psych. cost = psychological cost. Decr. = decrease, Incr. = increase.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 7

Standardized Path Coefficients for Predictors of Initial Motivations and Motivational Changes in Study 1b

Predictors	T1	ΔT2T1	ΔT3T2	ΔT4T3
Expectancy				
Female	−.16***	−.11**	−.04	−.03
SES	−.03	.02	.02	.01
High school GPA	.24***	.09*	.15***	.11*
Preparatory course	−.05	.01	.03	.00
Math2	−.15***	.29***	−.15**	−.27***
Teacher1	−.09*	.18***	.01	−.05
Teacher2	−.08*	.31***	−.18***	−.17**
Intrinsic value				
Female	−.02	−.06†	−.03	−.02
SES	−.03	.08*	−.04	.00
High school GPA	.18***	.10*	.07*	.07
Preparatory course	.05	.04	.03	−.02
Math2	−.16***	.28***	−.07†	−.20**
Teacher1	−.12**	.20***	−.04	−.07
Teacher2	−.10*	.24***	−.17***	−.10†
Utility value				
Female	−.03	−.03	−.05	−.02
SES	.00	.07*	.06	−.01
High school GPA	.07*	.05	.08*	.00
Preparatory course	.10*	.02	.02	−.06
Math2	−.31***	.11**	−.15**	−.22**
Teacher1	−.24***	.09**	−.03	−.09†
Teacher2	−.30**	.13***	−.12**	−.08
Psychological cost				
Female	.15***	−.03	.07*	.01
SES	−.05	−.01	−.02	.06
High school GPA	−.11**	.08*	−.03	−.09†
Preparatory course	−.03	−.03	−.06	.11*
Math2	.30***	−.32***	.07	.15*
Teacher1	.18***	−.12***	−.05	.02
Teacher2	.17***	−.22***	.14***	.04
Effort cost				
Female	.07†	−.02	.06†	−.03
SES	.00	.03	−.04	−.01
High school GPA	−.11**	.09**	−.04	−.04
Preparatory course	.03	.02	−.07*	.05
Math2	.25***	−.43***	.06	.20**
Teacher1	.09*	−.15***	−.06	.05
Teacher2	.12**	−.30***	.12**	.09

Note. Predictive effects of levels of motivation on motivational changes (T1 → ΔT2T1, T2 → ΔT3T2, T3 → ΔT4T3) as well as predictive effects of early motivational changes on subsequent changes (ΔT2T1 → ΔT3T2, ΔT3T2 → ΔT4T3) are not shown. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. Math2, Teacher1 and Teacher2 = dummy variables for the respective math courses and study programs.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 8

Predictive Effects of Delayed Performance Feedback on Motivational Changes in Study 1b

Predictors	T1	ΔT2T1	ΔT3T2	ΔT4T3
Expectancy				
Female	−.19**	−.12†	−.14*	.04
SES	.01	−.03	−.01	.03
High school GPA	.07	.06	.16**	.07
Preparatory course	−.10†	.10	.01	−.02
Math2	.02	−.15*	.09	.01
Delayed feedback	−.07	.14*	.08	−.03
Intrinsic value				
Female	−.03	−.01	−.05	.04
SES	.04	−.01	−.11†	.05
High school GPA	.09	.10	.02	−.05
Preparatory course	−.04	.07	−.02	−.04
Math2	.01	−.05	.21***	−.01
Delayed feedback	−.10	.05	−.01	−.03
Utility value				
Female	−.08	.02	−.01	−.08
SES	.04	−.03	.09	.07
High school GPA	−.02	.08†	.05	−.07
Preparatory course	.10	−.01	−.04	−.10
Math2	.13*	−.06	.05	−.06
Delayed feedback	−.08	.06	.01	−.04
Psychological cost				
Female	.13*	−.09†	.14*	.04
SES	−.11†	−.07	.05	.00
High school GPA	−.08	.09	−.04	−.13†
Preparatory course	.02	−.10†	−.01	.22**
Math2	.04	−.01	−.14*	.11†
Delayed feedback	.06	−.12*	−.02	.07
Effort cost				
Female	.07	−.08	.14*	.07
SES	.00	−.02	.07	−.01
High school GPA	−.07	.09	.00	−.05
Preparatory course	.10	−.01	−.06	.13†
Math2	.05	.00	−.15*	.10
Delayed feedback	−.01	−.14*	−.07	.04

Note. $n = 296$. Predictive effects of levels of motivation on motivational changes (T1 → ΔT2T1, T2 → ΔT3T2, T3 → ΔT4T3) as well as predictive effects of early motivational changes on subsequent changes (ΔT2T1 → ΔT3T2, ΔT3T2 → ΔT4T3) are not shown. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. Math2 = dummy variable for the respective math course and study program.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 9

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in Study 1b

Model and predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Covariates	[a]	[a]	[a]	
R^2	.11	.27	.24	
Expectancy				
T1	$.64^{***}$	$.33^{***}$	$-.22^{***}$	0.80
ΔT2T1	$.40^{***}$	$.38^{***}$	$-.23^{**}$	0.80
ΔT3T2	$.26^{**}$	$.20^{**}$	$-.29^{***}$	0.75
ΔT4T3	.09	.02	$-.14^{*}$	0.87
R^2	.41	.39	.30	
Intrinsic value				
T1	$.55^{***}$	$.26^{***}$	$-.22^{***}$	0.80
ΔT2T1	$.37^{***}$	$.20^{\dagger}$	$-.26^{***}$	0.77
ΔT3T2	$.28^{***}$	$.17^{\dagger}$	$-.29^{***}$	0.75
ΔT4T3	.04	.02	$-.14^{*}$	0.87
R^2	.33	.34	.29	
Utility value				
T1	$.47^{***}$	$.23^{**}$	.00	1.00
ΔT2T1	$.37^{**}$	$.26^{*}$	−.05	0.95
ΔT3T2	$.30^{**}$	$.21^{*}$	−.09	0.91
ΔT4T3	.11	−.02	$-.14^{*}$	0.87
R^2	.20	.32	.25	
Psychological cost				
T1	$-.58^{***}$	$-.40^{***}$	$.15^{*}$	1.16
ΔT2T1	$-.44^{***}$	$-.41^{***}$	.11	1.12
ΔT3T2	−.14	$-.29^{**}$	.09	1.09
ΔT4T3	.01	$-.13^{\dagger}$	.07	1.07
R^2	.31	.34	.25	
Effort cost				
T1	$-.38^{***}$	$-.37^{***}$	$.09^{\dagger}$	1.10
ΔT2T1	$-.30^{**}$	$-.28^{**}$	.02	1.02
ΔT3T2	$-.15^{\dagger}$	$-.24^{**}$	.00	1.00
ΔT4T3	−.03	$-.20^{**}$	.00	1.00
R^2	.20	.35	.24	

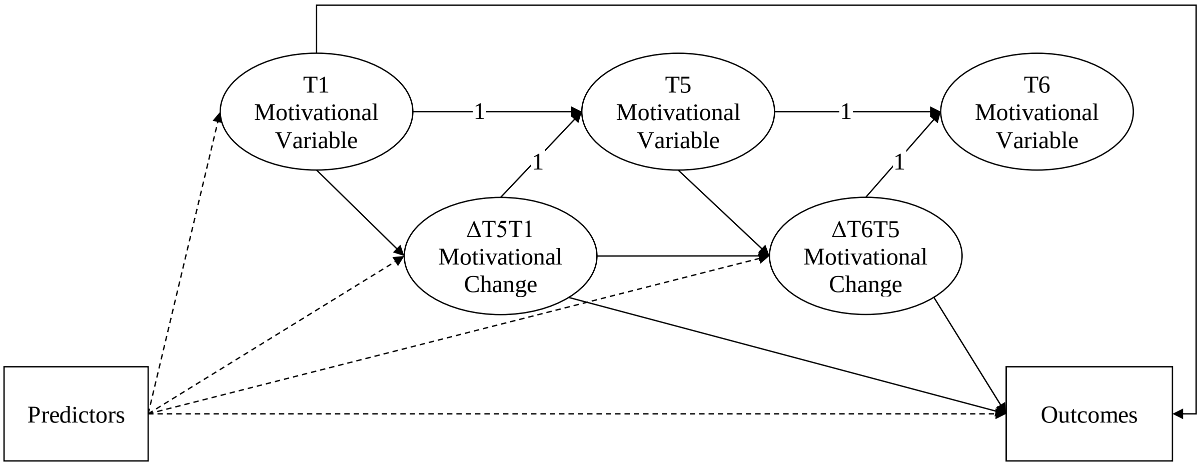
Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set focused on the prediction of course dropout. *OR* = odds ratio. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

[a] Covariates were students' gender, SES, high school GPA, participation in preparatory courses, and dummies for the math courses. See online supplemental material for full results, including all covariates.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 1

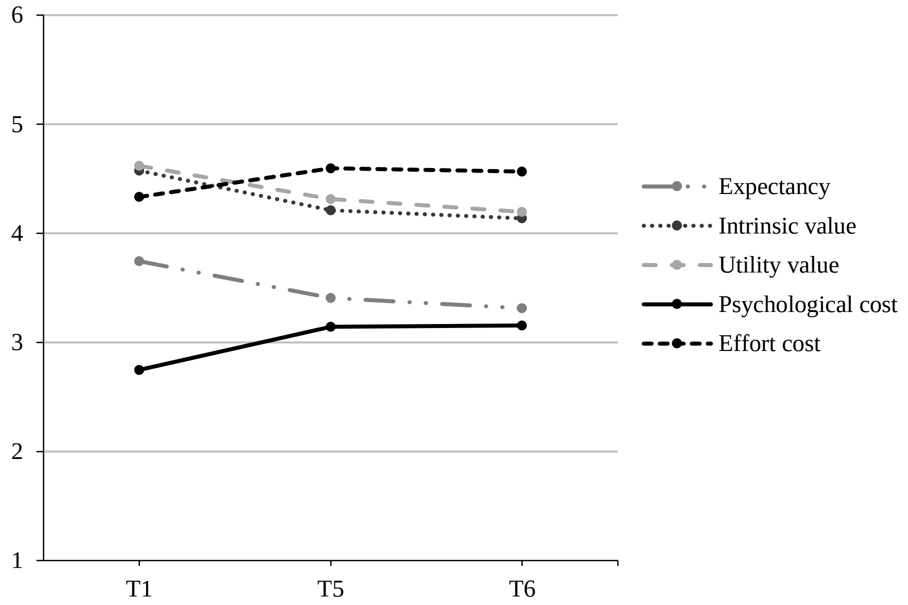
Latent Change Model Including Initial Levels of Motivation, Motivational Changes, and Predictor and Outcome Variables in Study 1a



Note. Motivational variables were the five expectancy-value constructs. Analogous models were modeled for each expectancy-value construct. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15). ΔT5T1 = motivational change from the beginning to the midpoint of the semester, ΔT6T5 = motivational change from the midpoint to the end of the semester.

Figure 2

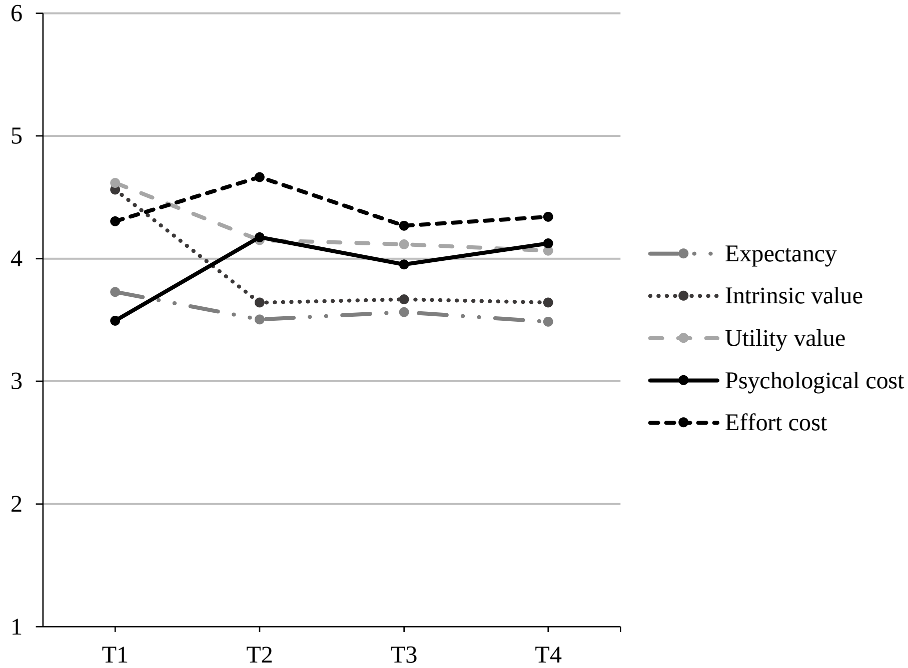
Trajectories of Students' Expectancy and Subjective Task Values in Study 1a



Note. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

Figure 3

Trajectories of Students' Expectancy and Subjective Task Values in Study 1b



Note. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

Supplemental Materials:

Students' Motivational Trajectories and Academic Success in Math-Intensive Study Programs: Why Short-Term Motivational Assessments Matter

Supplement S1. Full List of Self-Report Items Used in Study 1a and Study 1b

Table S1

List of Self-Report Items Used in Study 1a and Study 1b

Construct	Instruction and items (translated from German)
Course-specific expectancy-value beliefs (Weeks 2, 8, and 15)	
Expectancy	Based on my experiences in this class, I think I will do well on the exam.[a]
	Based on my experiences in this class, I think I am good at my major.[a]
	Based on my experiences in this class, I think I will perform at a high level.[a]
Intrinsic value	Doing the coursework and the assignments for this class is something I enjoy.[a]
	Doing the coursework and the assignments for this class is interesting.[a]
Utility value	Doing the coursework and the assignments for this class is useful for my future.[a]
	Doing the coursework and the assignments for this class is important because one just needs the content.[a]
Psychological cost	Doing the coursework and the assignments for this class is stressful for me.[a]
	Doing the coursework and the assignments for this class makes me really nervous.[a]
Effort cost	Doing the coursework and the assignments for this class is exhausting for me.[a]
	Doing the coursework and the assignments for this class drains a lot of my energy.[a]
Situation-specific expectancy-value beliefs in Study 1b (Weeks 3–5)	Think about the current worksheet you have turned in this week:
Expectancy	If the content of the current worksheet comes up on the exam: How well do you think will you perform on the exam?[b]
Intrinsic value	Doing this week's assignments is something I enjoyed.[a]
Utility value	Doing this week's assignments was generally useful.[a]
Psychological cost	Doing this week's assignments was stressful for me.[a]
Effort cost	Doing this week's assignments drained a lot of my energy.[a]
Study program satisfaction	I am certain that my study program is the right choice for me.[c]
	I am certain that my study program is a good fit for me.[c]
	In general, I am very satisfied with my study program.[a]
	In general, I am satisfied with the type of work in my study program.[a]
	I oftentimes think about dropping out of or switching my study program.[a]

Note. [a] 6-point scale ranging from 1 = *completely disagree* to 6 = *completely agree*. [b] 6-point scale ranging from 1 = *very poorly* to 6 = *very well*. [c] 6-point scale ranging from 1 = *very uncertain* to 6 = *very certain.*

Supplement S2. Tests of Measurement Invariance Across Study Programs, Gender, SES, Participation in Preparatory Math Courses, and Time in Study 1a

In the following tables, tests of measurement invariance across students' study programs, gender, family background (SES), and participation in preparatory math courses as well as across time are reported. In the configural model, the factor structure was constrained to be equal across groups or time. The model testing weak invariance was specified by additionally constraining the factor loadings to be equal across groups or time. Finally, in the model testing strong measurement invariance, item intercepts were additionally constrained to be the same across groups or time.

Table S2.1

Multigroup Analyses by Study Program in Study 1a

Models and Time Points	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
T1								
Configural[a]	211.00	105	.974	.959	.058	.051	—	—
Weak[a]	217.37	117	.976	.966	.054	.056	−.002	.004
Strong (partial)[ab]	250.54	127	.970	.961	.057	.061	.006	−.003
T5								
Configural[a]	156.48	105	.988	.981	.046	.035	—	—
Weak[a]	170.73	117	.987	.982	.045	.046	.001	.001
Strong[a]	228.37	129	.977	.970	.058	.056	.010	−.013
T6								
Configural[a]	136.77	105	.989	.983	.042	.035	—	—
Weak[a]	162.50	117	.985	.979	.047	.056	.004	−.005
Strong (partial)[abc]	187.17	126	.980	.973	.053	.066	.005	−.006

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] The error variance for one of the items assessing utility value was estimated to be very close to zero and not significant, and had negative values in some of our models. This error variance was therefore fixed at zero for the multigroup analyses.

[b] The intercept of one item assessing psychological cost was freely estimated across groups.

[c] The intercept of one item assessing expectancy was freely estimated in the math teacher education group.

Table S2.2

Multigroup Analyses by Gender in Study 1a

Models and Time Points	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
T1								
Configural	173.87	68	.974	.958	.059	.041	—	—
Weak	184.77	74	.973	.959	.058	.046	.001	.001
Strong	199.63	80	.970	.959	.058	.047	.003	.000
T5								
Configural	119.23	68	.987	.979	.047	.030	—	—
Weak	128.17	74	.986	.979	.047	.036	.001	.000
Strong	142.88	80	.984	.978	.048	.036	.002	−.001
T6								
Configural	107.19	68	.987	.978	.048	.030		
Weak	112.13	74	.987	.981	.046	.035	.000	.002
Strong	122.45	80	.985	.980	.046	.037	.002	.000

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

Table S2.3

Multigroup Analyses by Family Background (SES) in Study 1a

Models and Time Points	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
T1								
Configural	170.54	68	.970	.951	.062	.044	—	—
Weak	176.16	74	.970	.956	.059	.048	.000	.003
Strong	179.97	80	.971	.960	.056	.049	−.001	.003
T5								
Configural	122.37	68	.984	.975	.052	.031	—	—
Weak	130.55	74	.984	.976	.051	.038	.000	.001
Strong	133.23	80	.985	.979	.047	.038	−.001	.004
T6								
Configural[a]	113.33	70	.984	.974	.053	.034	—	—
Weak[a]	120.52	76	.983	.976	.051	.042	.001	.002
Strong[a]	124.25	82	.984	.979	.048	.040	−.001	.003

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] The error variance for one of the items assessing psychological cost was estimated to be very close to zero and not significant, and had negative values in some of our models. This error variance was therefore fixed at zero for the multigroup analysis at T6.

Table S2.4

Multigroup Analyses by Participation in Preparatory Math Courses in Study 1a

Models and Time Points	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
T1								
Configural	136.52	68	.979	.966	.052	.037	—	—
Weak	143.64	74	.979	.969	.050	.042	.000	.002
Strong	147.21	80	.980	.972	.047	.044	−.001	.003
T5								
Configural	130.77	68	.984	.975	.052	.032	—	—
Weak	135.96	74	.984	.977	.050	.036	.000	.002
Strong	144.04	80	.984	.978	.049	.037	.000	.001
T6								
Configural	88.27	68	.992	.987	.036	.032	—	—
Weak	91.77	74	.993	.989	.032	.036	−.001	.004
Strong	98.14	80	.993	.990	.031	.036	.000	.001

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

Table S2.5

Tests of Measurement Invariance Across Time in Study 1a

Models	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
Freely estimated parameters (configural)[a]	534.83	358	.988	.982	.022	.032	—	—
Fixed factor loadings (weak)[a]	536.50	370	.988	.983	.022	.033	.000	.000
Fixed factor loadings and item intercepts (strong)[a]	575.71	382	.986	.981	.023	.034	−.002	.001

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

[a] The error variances for one item assessing utility value at time points T5 and T6 were estimated to be very close to zero and not significant. Therefore, we removed the correlated residual for this item from the model.

Supplement S3. Plausible Values by Study Program in Study 1a and Study 1b

Table S3.1

Percentages of Students with Significant Motivational Changes by Math Course (Instructor) in Study 1a

Variable	ΔT5T1		ΔT6T5	
	Decrease	Increase	Decrease	Increase
Expectancy				
Physics1 [a]	27% (91%)	3% (9%)	6% (29%)	6% (71%)
Physics2 [a]	26% (89%)	2% (11%)	1% (40%)	3% (60%)
Math1	12% (61%)	7% (39%)	15% (85%)	1% (15%)
Math2	32% (83%)	2% (17%)	10% (71%)	4% (29%)
Teacher1	14% (72%)	2% (28%)	4% (62%)	4% (38%)
Teacher2	9% (67%)	7% (33%)	6% (87%)	1% (13%)
Intrinsic value				
Physics1 [a]	28% (92%)	1% (8%)	2% (33%)	4% (67%)
Physics2 [a]	21% (89%)	0% (11%)	3% (34%)	1% (66%)
Math1	5% (54%)	1% (46%)	10% (84%)	0% (16%)
Math2	22% (87%)	1% (13%)	11% (70%)	1% (30%)
Teacher1	11% (76%)	2% (24%)	2% (22%)	7% (78%)
Teacher2	9% (54%)	5% (46%)	4% (85%)	1% (15%)
Utility value				
Physics1 [a]	14% (88%)	1% (12%)	3% (42%)	4% (58%)
Physics2 [a]	14% (87%)	0% (13%)	1% (40%)	3% (60%)
Math1	5% (65%)	1% (35%)	4% (75%)	0% (24%)
Math2	12% (72%)	1% (29%)	6% (73%)	1% (26%)
Teacher1	11% (79%)	3% (21%)	2% (42%)	4% (58%)
Teacher2	2% (17%)	17% (83%)	18% (95%)	0% (5%)
Psychological cost				
Physics1 [a]	2% (9%)	33% (91%)	4% (62%)	4% (38%)
Physics2 [a]	1% (9%)	25% (91%)	2% (58%)	2% (42%)
Math1	2% (34%)	15% (66%)	6% (39%)	9% (62%)
Math2	4% (34%)	16% (66%)	5% (52%)	6% (47%)
Teacher1	11% (33%)	10% (67%)	6% (52%)	4% (48%)
Teacher2	4% (39%)	6% (61%)	2% (33%)	1% (67%)
Effort cost				
Physics1 [a]	2% (11%)	33% (90%)	6% (51%)	5% (49%)
Physics2 [a]	1% (10%)	23% (90%)	5% (57%)	4% (43%)
Math1	7% (38%)	17% (62%)	8% (53%)	9% (46%)
Math2	11% (52%)	11% (48%)	7% (60%)	4% (40%)
Teacher1	14% (47%)	10% (53%)	6% (65%)	4% (34%)
Teacher2	16% (67%)	6% (33%)	1% (42%)	2% (59%)

Note. Plausible values were generated for each latent change score using Bayesian estimation to determine the number of students experiencing significant changes in their expectancy-value beliefs. The number of students with negative and positive change scores is shown in parentheses. Physics1, Physics2, Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Both courses were taught by the same instructor.

Table S3.2

Percentages of Students with Significant Motivational Changes by Math Course (Instructor) in Study 1b

Variable	ΔT2T1		ΔT3T2		ΔT4T3	
	Decrease	Increase	Decrease	Increase	Decrease	Increase
Expectancy						
Physics1 [a]	34% (79%)	8% (18%)	13% (30%)	22% (67%)	11% (37%)	13% (59%)
Physics2 [a]	43% (86%)	5% (11%)	8% (17%)	36% (81%)	28% (70%)	10% (27%)
Math2	18% (37%)	26% (55%)	28% (66%)	12% (26%)	24% (56%)	13% (38%)
Teacher1	23% (55%)	18% (41%)	12% (37%)	23% (57%)	19% (54%)	14% (41%)
Teacher2	6% (22%)	26% (73%)	35% (90%)	5% (10%)	17% (34%)	21% (63%)
Intrinsic value						
Physics1 [a]	58% (95%)	3% (6%)	13% (35%)	22% (62%)	9% (32%)	17% (66%)
Physics2 [a]	62% (92%)	3% (5%)	12% (21%)	37% (77%)	31% (74%)	9% (23%)
Math2	38% (71%)	12% (24%)	28% (68%)	15% (30%)	22% (55%)	20% (42%)
Teacher1	40% (79%)	7% (17%)	26% (59%)	19% (38%)	20% (51%)	23% (42%)
Teacher2	32% (72%)	12% (26%)	38% (84%)	6% (15%)	11% (29%)	27% (71%)
Utility value						
Physics1 [a]	50% (86%)	3% (11%)	11% (42%)	19% (55%)	11% (39%)	14% (57%)
Physics2 [a]	52% (87%)	5% (10%)	12% (32%)	27% (67%)	27% (66%)	14% (33%)
Math2	29% (50%)	26% (46%)	31% (65%)	15% (32%)	21% (56%)	17% (39%)
Teacher1	23% (52%)	22% (38%)	21% (56%)	16% (39%)	13% (49%)	14% (46%)
Teacher2	15% (42%)	31% (54%)	29% (76%)	13% (22%)	15% (31%)	18% (65%)
Psychological cost						
Physics1 [a]	6% (13%)	49% (87%)	19% (54%)	16% (42%)	18% (66%)	13% (32%)
Physics2 [a]	4% (7%)	65% (92%)	48% (86%)	5% (11%)	8% (18%)	42% (81%)
Math2	28% (45%)	26% (50%)	20% (38%)	29% (58%)	18% (39%)	28% (58%)
Teacher1	12% (33%)	32% (60%)	32% (61%)	17% (35%)	16% (49%)	19% (47%)
Teacher2	28% (61%)	20% (37%)	18% (24%)	38% (77%)	24% (71%)	10% (24%)
Effort cost						
Physics1 [a]	7% (18%)	46% (80%)	27% (75%)	6% (24%)	19% (68%)	12% (30%)
Physics2 [a]	4% (7%)	58% (91%)	55% (94%)	5% (6%)	8% (20%)	32% (77%)
Math2	37% (68%)	14% (27%)	23% (45%)	26% (53%)	18% (42%)	29% (56%)
Teacher1	15% (34%)	28% (62%)	34% (70%)	13% (28%)	21% (40%)	24% (53%)
Teacher2	29% (71%)	12% (24%)	11% (24%)	27% (73%)	23% (72%)	11% (26%)

Note. Plausible values were generated for each latent change score using Bayesian estimation to determine the number of students experiencing significant changes in their expectancy-value beliefs. The number of students with negative and positive change scores is shown in parentheses. Physics1, Physics2, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

[a] Both courses were taught by the same instructor.

Supplement S4. Wald Tests of Parameter Constraints for Motivational Changes in Study 1a and Study 1b

Table S4.1

Parameter Constraints for Latent Change Scores Within and Between the Five Expectancy-Value Constructs in Study 1a

Parameter constraints	ΔM_1	ΔM_2	Wald Test	*p*
Changes within constructs across time				
Expectancy: ΔM_1 (ΔT5T1) = ΔM_2 (ΔT6T5)	−0.34	−0.09	27.19***	<.001
Intrinsic value: ΔM_1 (ΔT5T1) = ΔM_2 (ΔT6T5)	−0.36	−0.08	25.02***	<.001
Utility value: ΔM_1 (ΔT5T1) = ΔM_2 (ΔT6T5)	−0.30	−0.12	7.08**	.008
Psychological cost: ΔM_1 (ΔT5T1) = ΔM_2 (ΔT6T5)	0.40	0.01	35.34***	<.001
Effort cost: ΔM_1 (ΔT5T1) = ΔM_2 (ΔT6T5)	0.26	−0.03	21.64***	<.001
Changes between constructs from T1 to T5				
ΔM_1 (Expectancy ΔT5T1) = ΔM_2 (Intrinsic value ΔT5T1)	−0.34	−0.36	0.51	.476
ΔM_1 (Expectancy ΔT5T1) = ΔM_2 (Utility value ΔT5T1)	−0.34	−0.30	0.54	.461
ΔM_1 (Expectancy ΔT5T1) = $-\Delta M_2$ (Psychological cost ΔT5T1)	−0.34	0.40	2.12	.145
ΔM_1 (Expectancy ΔT5T1) = $-\Delta M_2$ (Effort cost ΔT5T1)	−0.34	0.26	2.98†	.084
ΔM_1 (Intrinsic value ΔT5T1) = ΔM_2 (Utility value ΔT5T1)	−0.36	−0.30	1.99	.159
ΔM_1 (Intrinsic value ΔT5T1) = $-\Delta M_2$ (Psychological cost ΔT5T1)	−0.36	0.40	0.52	.471
ΔM_1 (Intrinsic value ΔT5T1) = $-\Delta M_2$ (Effort cost ΔT5T1)	−0.36	0.26	3.96*	.047
ΔM_1 (Utility value ΔT5T1) = $-\Delta M_2$ (Psychological cost ΔT5T1)	−0.30	0.40	2.92†	.088
ΔM_1 (Utility value ΔT5T1) = $-\Delta M_2$ (Effort cost ΔT5T1)	−0.30	0.26	0.57	.452
ΔM_1 (Psychological cost ΔT5T1) = ΔM_2 (Effort cost ΔT5T1)	0.40	0.26	13.41***	<.001
Changes between constructs from T5 to T6				
ΔM_1 (Expectancy ΔT6T5) = ΔM_2 (Intrinsic value ΔT6T5)	−0.09	−0.08	0.22	.639
ΔM_1 (Expectancy ΔT6T5) = ΔM_2 (Utility value ΔT6T5)	−0.09	−0.12	0.24	.623
ΔM_1 (Expectancy ΔT6T5) = $-\Delta M_2$ (Psychological cost ΔT6T5)	−0.09	0.01	3.25†	.076
ΔM_1 (Expectancy ΔT6T5) = $-\Delta M_2$ (Effort cost ΔT6T5)	−0.09	−0.03	6.94**	.008
ΔM_1 (Intrinsic value ΔT6T5) = ΔM_2 (Utility value ΔT6T5)	−0.08	−0.12	0.88	.348
ΔM_1 (Intrinsic value ΔT6T5) = $-\Delta M_2$ (Psychological cost ΔT6T5)	−0.08	0.01	1.28	.258
ΔM_1 (Intrinsic value ΔT6T5) = $-\Delta M_2$ (Effort cost ΔT6T5)	−0.08	−0.03	3.71†	.054
ΔM_1 (Utility value ΔT6T5) = $-\Delta M_2$ (Psychological cost ΔT6T5)	−0.12	0.01	3.34†	.068
ΔM_1 (Utility value ΔT6T5) = $-\Delta M_2$ (Effort cost ΔT6T5)	−0.12	−0.03	6.40*	.011
ΔM_1 (Psychological cost ΔT6T5) = ΔM_2 (Effort cost ΔT6T5)	0.01	−0.03	1.05	.305

Note. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S4.2

Parameter Constraints for Latent Change Scores Within and Between the Five Expectancy-Value Constructs in Study 1b

Parameter constraints	ΔM_1	ΔM_2	ΔM_3	Wald Test	p
Changes within constructs across time (T1 through T4)					
Expectancy: ΔM_1 (ΔT2T1) + ΔM_2 (ΔT3T2) + ΔM_3 (ΔT4T3) = 0	−0.23	0.06	−0.08	33.30***	<.001
Intrinsic value: ΔM_1 (ΔT2T1) + ΔM_2 (ΔT3T2) + ΔM_3 (ΔT4T3) = 0	−0.92	0.03	−0.03	349.89***	<.001
Utility value: ΔM_1 (ΔT2T1) + ΔM_2 (ΔT3T2) + ΔM_3 (ΔT4T3) = 0	−0.47	−0.03	−0.05	111.19***	<.001
Psych. cost: ΔM_1 (ΔT2T1) + ΔM_2 (ΔT3T2) + ΔM_3 (ΔT4T3) = 0	0.68	−0.22	0.17	105.42***	<.001
Effort cost: ΔM_1 (ΔT2T1) + ΔM_2 (ΔT3T2) + ΔM_3 (ΔT4T3) = 0	0.35	−0.39	0.07	0.52	.472
Changes between constructs from T1 to T2					
ΔM_1 (Expectancy ΔT2T1) = ΔM_2 (Intrinsic value ΔT2T1)	−0.23	−0.92	—	190.29***	<.001
ΔM_1 (Expectancy ΔT2T1) = ΔM_2 (Utility value ΔT2T1)	−0.23	−0.47	—	18.83***	<.001
ΔM_1 (Expectancy ΔT2T1) = $-\Delta M_2$ (Psychological cost ΔT2T1)	−0.23	0.68	—	53.63***	<.001
ΔM_1 (Expectancy ΔT2T1) = $-\Delta M_2$ (Effort cost ΔT2T1)	−0.23	0.35	—	5.10*	.024
ΔM_1 (Intrinsic value ΔT2T1) = ΔM_2 (Utility value ΔT2T1)	−0.92	−0.47	—	69.01***	<.001
ΔM_1 (Intrinsic value ΔT2T1) = $-\Delta M_2$ (Psychological cost ΔT2T1)	−0.92	0.68	—	13.08***	<.001
ΔM_1 (Intrinsic value ΔT2T1) = $-\Delta M_2$ (Effort cost ΔT2T1)	−0.92	0.35	—	77.74***	<.001
ΔM_1 (Utility value ΔT2T1) = $-\Delta M_2$ (Psychological cost ΔT2T1)	−0.47	0.68	—	8.34**	.004
ΔM_1 (Utility value ΔT2T1) = $-\Delta M_2$ (Effort cost ΔT2T1)	−0.47	0.35	—	2.77†	.096
ΔM_1 (Psychological cost ΔT2T1) = ΔM_2 (Effort cost ΔT2T1)	0.68	0.35	—	40.58***	<.001

Note. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. Psych. cost = psychological cost.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Supplement S5. Model Fit of Latent Change Models for the Five Expectancy-Value Constructs Including Students' Study Program Satisfaction and Exam Performance in Study 1a and Study 1b

Table S5.1

Model Fit for Univariate Latent Change Models for the Five Expectancy-Value Constructs Including Study Program Satisfaction and Exam Performance in Study 1a

Model	χ^2	*df*	CFI	TLI	RMSEA	SRMR
Expectancy	272.27	158	.982	.974	.027	.032
Intrinsic value	261.27	97	.957	.927	.041	.034
Utility value	203.94	97	.965	.941	.033	.036
Psychological cost	256.45	97	.958	.930	.040	.041
Effort cost	178.79	97	.981	.969	.029	.031

Note. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

Table S5.2

Model Fit of the Latent Change Models for the Five Expectancy-Value Constructs Including Study Program Satisfaction and Exam Performance in Study 1b

Model	χ^2	*df*	CFI	TLI	RMSEA	SRMR
Expectancy	91.86	51	.980	.955	.032	.033
Intrinsic value	102.65	51	.970	.933	.036	.038
Utility value	103.23	51	.968	.928	.036	.037
Psychological cost	97.78	51	.974	.941	.034	.035
Effort cost	98.76	51	.973	.940	.035	.034

Note. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

Supplement S6. Standardized Path Coefficients for Predictors of Students' Study Program Satisfaction, Exam Performance, and Course Dropout Estimated in the Latent Change Models for the Five Expectancy-Value Constructs in Study 1a and Study 1b

Table S6.1

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Expectancy Model in Study 1a

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	.02	−.07†	−.09*	0.91
SES	−.01	.02	−.01	0.99
High school GPA	.08	.43***	−.30***	0.74
Preparatory course	.03	.02	−.19***	0.83
Math1	−.04	−.09†	−.04	0.96
Math2	−.09†	−.03	−.04	0.96
Teacher1	−.15**	.02	.13**	1.13
Teacher2	−.08†	.05	−.01	0.99
Expectancy T1	.62***	.31***	−.17***	0.84
Expectancy ΔT5T1	.39***	.27***	−.22***	0.81
Expectancy ΔT6T5	.18**	.14*	[a]	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).
[a] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Therefore, the analyses included only the latent change score from the beginning towards the midpoint of the semester. † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.2

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Intrinsic Value Model in Study 1a

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	−.11**	−.15***	−.05	0.95
SES	−.07	−.01	−.02	0.98
High school GPA	.11*	.48***	−.31***	0.74
Preparatory course	−.03	−.01	−.19***	0.83
Math1	−.08†	−.10†	−.01	0.99
Math2	−.09*	−.06	−.02	0.98
Teacher1	−.12**	.02	.11*	0.12
Teacher2	−.05	.06	−.01	0.99
Intrinsic value T1	.70***	.24***	−.18***	0.84
Intrinsic value ΔT5T1	.48***	.20**	−.23**	0.80
Intrinsic value ΔT6T5	.31***	.16*	[a]	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).
[a] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Therefore, the analyses included only the latent change score from the beginning towards the midpoint of the semester. † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.3

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Utility Value Model in Study 1a

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	−.10*	−.15***	−.05	0.96
SES	−.06	.02	−.02	0.98
High school GPA	.15*	.50***	−.38***	0.68
Preparatory course	−.01	−.01	−.19***	0.83
Math1	.02	−.09	−.04	0.96
Math2	−.02	−.06	.01	1.01
Teacher1	−.03	.06	.11**	1.12
Teacher2	.05	.07	−.01	0.99
Utility value T1	.49***	.18**	.04	1.04
Utility value ΔT5T1	.47***	.16†	−.07	0.93
Utility value ΔT6T5	.26*	.02	[a]	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Therefore, the analyses included only the latent change score from the beginning towards the midpoint of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.4

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Psychological Cost Model in Study 1a

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	−.06	−.10*	−.06	0.95
SES	−.05	−.01	−.02	0.98
High school GPA	.18**	.47***	−.36***	0.70
Preparatory course	−.02	−.02	−.18***	0.84
Math1	−.09†	−.11†	−.08†	0.93
Math2	−.14**	−.08	−.03	0.97
Teacher1	−.14**	.03	.09*	1.10
Teacher2	−.07	.05	−.05	0.95
Psychological cost T1	−.58***	−.35***	.11*	1.12
Psychological cost ΔT2T1	−.35***	−.23**	.04	1.04
Psychological cost ΔT3T2	−.11†	−.03	[a]	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Therefore, the analyses included only the latent change score from the beginning towards the midpoint of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.5

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Effort Cost Model in Study 1a

Predictors	Study satisfaction	Exam performance	Course dropout β	Course dropout *OR* (β)
Female	−.12**	−.12**	−.05	0.96
SES	−.03	.01	−.02	0.98
High school GPA	.24***	.50***	−.37***	0.69
Preparatory course	.01	−.01	−.18***	0.83
Math1	−.07	−.08	−.08†	0.93
Math2	−.17**	−.05	−.03	0.97
Teacher1	−.16**	.03	.10*	1.10
Teacher2	−.05	.07	−.05	0.95
Effort cost T1	−.42***	−.39***	.10*	1.10
Effort cost ΔT5T1	−.22**	−.17**	.03	1.03
Effort cost ΔT6T5	−.14*	−.09	[a]	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Therefore, the analyses included only the latent change score from the beginning towards the midpoint of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.6

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Expectancy Model in Study 1b

Predictors	Study program satisfaction	Exam performance	Course dropout β	Course dropout *OR* (β)
Female	.01	−.07	−.07	0.93
SES	−.06	.04	.01	1.01
High school GPA	.08	.43***	−.31***	0.74
Preparatory course	.03	−.02	−.18***	0.84
Math2	−.15**	−.13*	−.06	0.94
Teacher1	−.17**	.00	.12**	1.13
Teacher2	−.07	.03	−.08†	0.92
Expectancy T1	.64***	.33***	−.22***	0.80
Expectancy ΔT2T1	.40***	.38***	−.23**	0.80
Expectancy ΔT3T2	.26**	.20**	−.29***	0.75
Expectancy ΔT4T3	.09	.02	−.14*	0.87

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.7

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Intrinsic Value Model in Study 1b

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	−.10†	−.12*	−.06	0.94
SES	−.07	.03	.00	1.00
High school GPA	.11†	.49***	−.32***	0.73
Preparatory course	.03	−.03	−.17***	0.85
Math2	−.16**	−.10	−.04	0.96
Teacher1	−.14**	.03	.11*	1.12
Teacher2	−.03	.08	−.08†	0.93
Intrinsic value T1	.55***	.26***	−.22***	0.80
Intrinsic value ΔT2T1	.37***	.20†	−.26***	0.77
Intrinsic value ΔT3T2	.28***	.17†	−.29***	0.75
Intrinsic value ΔT4T3	.04	.02	−.14*	0.87

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.8

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Utility Value Model in Study 1b

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	−.09†	−.12*	−.03	0.97
SES	−.11†	.02	.01	1.01
High school GPA	.16*	.51***	−.38***	0.68
Preparatory course	.02	−.03	−.19***	0.83
Math2	−.12*	−.09	−.02	0.98
Teacher1	−.12*	.04	.12**	1.13
Teacher2	.02	.10†	−.05	0.96
Utility value T1	.47***	.23**	.00	1.00
Utility value ΔT2T1	.37**	.26*	−.05	0.95
Utility value ΔT3T2	.30**	.21*	−.09	0.91
Utility value ΔT4T3	.11	−.02	−.14*	0.87

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.9

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Psychological Cost Model in Study 1b

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	−.07	$-.10^{\dagger}$	−.05	0.96
SES	$-.12^{*}$	.01	.00	1.00
High school GPA	$.18^{**}$	$.50^{***}$	$-.37^{***}$	0.69
Preparatory course	.02	−.01	$-.18^{***}$	0.83
Math2	$-.20^{***}$	−.10	−.03	0.97
Teacher1	$-.14^{**}$	.04	$.11^{*}$	1.12
Teacher2	−.09	.07	−.06	0.94
Psychological cost T1	$-.58^{***}$	$-.40^{***}$	$.15^{*}$	1.16
Psychological cost ΔT2T1	$-.44^{***}$	$-.41^{***}$	.11	1.12
Psychological cost ΔT3T2	−.14	$-.29^{**}$	.09	1.09
Psychological cost ΔT4T3	.01	$-.13^{\dagger}$	.07	1.07

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.10

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Effort Cost Model in Study 1b

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	$-.09^{\dagger}$	$-.11^{*}$	−.04	0.96
SES	−.08	.03	.00	1.00
High school GPA	$.19^{**}$	$.50^{***}$	$-.37^{***}$	0.69
Preparatory course	.05	.01	$-.18^{***}$	0.83
Math2	$-.22^{**}$	−.07	−.03	0.97
Teacher1	$-.19^{***}$	.03	$.11^{*}$	1.12
Teacher2	−.07	.08	−.06	0.95
Effort cost T1	$-.38^{***}$	$-.37^{***}$	$.09^{\dagger}$	1.10
Effort cost ΔT2T1	$-.30^{**}$	$-.28^{**}$	.02	1.02
Effort cost ΔT3T2	$-.15^{\dagger}$	$-.24^{**}$	.00	1.00
Effort cost ΔT4T3	−.03	$-.20^{**}$	.00	1.00

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Supplement S7. Supplemental Analyses Concerning Missing Data in Study 1a and Study 1b

Two sets of supplemental analyses were conducted to describe the implications of missing data in both studies and to test the robustness of our findings. First, we tested the implications of including covariates as auxiliary variables in our latent change score models for the estimated change scores by estimating the models with and without auxiliary variables. The estimated latent change scores for students' expectancy and task values were similar to the original analyses, which included the covariates as auxiliary variables (see Tables S7.1 and S7.2). We also report the amount of variance in students' motivations and motivational changes that was explained by students' individual and background characteristics to show the strength of the associations between the covariates and the predicted outcomes.

Second, we replicated our latent change score analyses using only the subsample of students who were present for the end-of-term data collection (T6; Study 1a: n = 608 of 1,004; Study 1b: n = 439 of 773). Course dropout/Non-attendance at T6 was linked to lower SES ($r = -.11$, $p = .002$), lower high school GPA ($r = -.39$, $p < .001$), and non-participation in preparatory math courses ($r = -.23$, $p < .001$; see Table 1). The estimated means and variances of the latent change scores for this subsample of students versus for the full sample in our original analysis are shown in Table S7.3 for Study 1a and Table S7.4 for Study 1b. For Study 1a, motivational changes from the beginning towards the midpoint of the semester (ΔT5T1) are somewhat smaller compared to the original analysis that included all students. This pattern of results suggests that students who dropped out of their math course were at risk of experiencing somewhat greater motivational declines compared to students who did not drop out.

Table S7.1

Latent Means and Variances of Initial Motivations and Latent Change Scores With and Without Auxiliary Variables in Study 1a

Variable	T1		ΔT5T1		ΔT6T5	
	M	σ^2	*M*	σ^2	*M*	σ^2
Repeated analysis **without** auxiliary variables						
Expectancy	3.75	0.69^{***}	-0.32^{***}	0.44^{***}	-0.10^{**}	0.29^{***}
Intrinsic value	4.58	0.54^{***}	-0.34^{***}	0.51^{***}	-0.08^{*}	0.32^{***}
Utility value	4.62	0.88^{***}	-0.30^{***}	0.67^{***}	-0.08^{*}	0.37^{***}
Psychological cost	2.78	1.01^{***}	0.37^{***}	0.68^{***}	0.02	0.44^{***}
Effort cost	4.33	1.02^{***}	0.25^{***}	0.84^{***}	−0.02	0.45^{***}
Original analysis **including** all covariates as auxiliary variables						
Expectancy	3.74	0.69^{***}	-0.34^{***}	0.45^{***}	-0.09^{**}	0.30^{***}
Intrinsic value	4.57	0.54^{***}	-0.36^{***}	0.52^{***}	-0.08^{*}	0.33^{***}
Utility value	4.62	0.88^{***}	-0.30^{***}	0.67^{***}	-0.12^{**}	0.39^{***}
Psychological cost	2.75	1.01^{***}	0.40^{***}	0.69^{***}	0.01	0.44^{***}
Effort cost	4.33	1.02^{***}	0.26^{***}	0.83^{***}	−0.03	0.45^{***}
Amount of **variance explained** by covariates (gender, SES, high school GPA, preparatory math courses, course dummies)						
Expectancy	$R^2 = .089$		$R^2 = .112$		$R^2 = .059$	
Intrinsic value	$R^2 = .112$		$R^2 = .137$		$R^2 = .113$	
Utility value	$R^2 = .168$		$R^2 = .124$		$R^2 = .126$	
Psychological cost	$R^2 = .103$		$R^2 = .120$		$R^2 = .020$	
Effort cost	$R^2 = .058$		$R^2 = .126$		$R^2 = .026$	

Note. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S7.2

Latent Means and Variances of Initial Motivations and Latent Change Scores With and Without Auxiliary Variables in Study 1b

Variable	T1		ΔT2T1		ΔT3T2		ΔT4T3	
	M	σ^2	*M*	σ^2	*M*	σ^2	*M*	σ^2
Repeated analysis **without** auxiliary variables								
Expectancy	3.73	0.83***	−0.21***	1.01***	0.06	1.05***	−0.08†	0.96***
Intrinsic value	4.56	0.77***	−0.90***	1.52***	0.01	1.58***	−0.02	1.38***
Utility value	4.62	1.27***	−0.46***	1.79***	−0.04	1.28***	−0.05	1.03***
Psychological cost	3.50	1.81***	0.67***	2.54***	−0.22**	1.99***	0.19**	1.87***
Effort cost	4.31	1.32***	0.34***	1.92***	−0.39***	1.70***	0.09†	1.62***
Original analysis **including** all covariates as auxiliary variables								
Expectancy	3.73	0.83***	−0.23***	0.99***	0.06	1.06***	−0.08†	0.97***
Intrinsic value	4.56	0.77***	−0.92***	1.52***	0.03	1.58***	−0.03	1.37***
Utility value	4.62	1.27***	−0.47***	1.81***	−0.03	1.28***	−0.05	1.03***
Psychological cost	3.49	1.82***	0.68***	2.49***	−0.22***	2.01***	0.17**	1.88***
Effort cost	4.30	1.33***	0.35***	1.85***	−0.39***	1.71***	0.07	1.63***
Amount of **variance explained** by covariates (gender, SES, high school GPA, preparatory math courses, course dummies)								
Expectancy	R^2 = .092		R^2 = .147		R^2 = .148		R^2 = .011	
Intrinsic value	R^2 = .060		R^2 = .157		R^2 = .141		R^2 = .031	
Utility value	R^2 = .160		R^2 = .147		R^2 = .066		R^2 = .011	
Psychological cost	R^2 = .119		R^2 = .212		R^2 = .143		R^2 = .050	
Effort cost	R^2 = .063		R^2 = .264		R^2 = .177		R^2 = .048	

Note. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. T6 = end-of-term (Week 15).
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S7.3

Latent Means and Variances of Initial Motivations and Latent Change Scores Using the Full Sample or a Subsample of Students who were Present at the End of the Semester in Study 1a

Variable	T1		ΔT5T1		ΔT6T5	
	M	σ^2	*M*	σ^2	*M*	σ^2
Original analysis **with full sample** (*N* = 1,004)						
Expectancy	3.74	0.69***	−0.34***	0.45***	−0.09**	0.30***
Intrinsic value	4.57	0.54***	−0.36***	0.52***	−0.08*	0.33***
Utility value	4.62	0.88***	−0.30***	0.67***	−0.12**	0.39***
Psychological cost	2.75	1.01***	0.40***	0.69***	0.01	0.44***
Effort cost	4.33	1.02***	0.26***	0.83***	−0.03	0.45***
Only including **students who were present at T6** (*n* = 608)						
Expectancy	3.85	0.60***	−0.27***	0.43***	−0.12***	0.29***
Intrinsic value	4.70	0.41***	−0.29***	0.46***	−0.12***	0.31***
Utility value	4.61	0.70***	−0.24***	0.60***	−0.10*	0.36***
Psychological cost	2.59	0.90***	0.37***	0.62***	0.02	0.43***
Effort cost	4.27	1.04***	0.25***	0.83***	−0.03	0.45***

Note. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S7.4

Latent Means and Variances of Initial Motivations and Latent Change Scores Using the Full Sample or Subsample of Students Present at the End of the Semester in Study 1b

Variable	T1		ΔT2T1		ΔT3T2		ΔT4T3	
	M	σ^2	*M*	σ^2	*M*	σ^2	*M*	σ^2
Original analysis **with full sample** (N = 773)								
Expectancy	3.73	0.83^{***}	-0.23^{***}	0.99^{***}	0.06	1.06^{***}	$-0.08^{\dagger}$	0.97^{***}
Intrinsic value	4.56	0.77^{***}	-0.92^{***}	1.52^{***}	0.03	1.58^{***}	−0.03	1.37^{***}
Utility value	4.62	1.27^{***}	-0.47^{***}	1.81^{***}	−0.03	1.28^{***}	−0.05	1.03^{***}
Psychological cost	3.49	1.82^{***}	0.68^{***}	2.49^{***}	-0.22^{***}	2.01^{***}	0.17^{**}	1.88^{***}
Effort cost	4.30	1.33^{***}	0.35^{***}	1.85^{***}	-0.39^{***}	1.71^{***}	0.07	1.63^{***}
Only including **students who were present at T6** (n = 439)								
Expectancy	3.86	0.80^{***}	-0.20^{***}	0.99^{***}	0.12^{*}	1.06^{***}	$-0.09^{\dagger}$	0.91^{***}
Intrinsic value	4.68	0.61^{***}	-0.86^{***}	1.62^{***}	0.05	1.58^{***}	−0.01	1.27^{***}
Utility value	4.63	1.15^{***}	-0.44^{***}	1.68^{***}	−0.03	1.25^{***}	−0.01	1.00^{***}
Psychological cost	3.39	1.80^{***}	0.69^{***}	2.54^{***}	-0.23^{**}	1.87^{***}	0.19^{**}	1.63^{***}
Effort cost	4.24	1.41^{***}	0.36^{***}	1.91^{***}	-0.44^{***}	1.68^{***}	$0.12^{\dagger}$	1.62^{***}

Note. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. T6 = end-of-term (Week 15).
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.